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RAGE AGAINST THE MACHINES: LABOR-SAVING TECHNOLOGY AND UNREST IN INDUSTRIALIZING ENGLAND

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JEL Classification: P16, J21, J43, N33

Keywords: Labor-saving technology, social instability, riots, welfare support, agricultural technology, factor prices and technological change

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Rage Against the Machines: Labor-Saving Technology and Unrest in Industrializing England *

Bruno Caprettini Hans-Joachim Voth

September 30, 2019

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Can new technology cause social instability and unrest? We examine the famous 'Captain Swing' riots in 1830s England. Newly-collected data on threshing machine diffusion shows that labor-saving technology was associated with more riots. We instrument technology adoption with the share of heavy soils in a parish: IV estimates show that threshing machines were an important cause of unrest. Where alternative employment opportunities softened the blow of new technology, there was less rioting. In areas affected by the Swing riots in 1830-32, technology adoption and patenting rates slowed down for decades thereafter.

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Introduction

From the invention of steam engines to the IT revolution, the adoption of new technologies has gone hand-in-hand with massive job destruction. Spinners and weavers were made redundant by steam-powered textile mills 200 year ago; more recently, computers have replaced phone operators, bookkeepers and other workers performing routine jobs (Autor et al., 2003). While the vast increase in living standards over the last 200 years owes a great deal to new technology (Mokyr, 1992), labor-saving technologies have put downward pressure on low-skilled workers' wages (Acemoglu and Autor, 2011). At the same time, they have driven up the demand for highly-skilled workers operating the new equipment (Autor et al., 1998; Acemoglu and Restrepo, 2018), increasing inequality.

Classical economists long predicted that technological unemployment would lead to social and political instability. Keynes (1931) and Leontief (1952) argued that technological unemployment would prove to be a first-order problem; Marx (1867) thought that technological change would depress wages to the point where workers would revolt. And yet, while there is ample evidence that labor-saving technical change can adversely affect workers' employment and wages, its social and political consequences are largely unexplored.[1].

In this paper, we examine whether the introduction of labor-saving technology can cause social instability and political unrest. In addition, we analyze the consequences of technology-induced unrest on innovation and technology adoption. We do so by looking at one famous historical episode – the 'Captain Swing' riots in 1830s England. These riots constitute the largest wave of political unrest in English history, with more than 3,000 cases of arson, looting, attacks on authorities, and machine-breaking across 45 counties. The riots had lasting consequences, ushering in a period of institutional reform (Aidt and Franck, 2015).

Using newly-collected historical data on the diffusion of threshing machines, we show that labor-saving technology was a key factor behind the riots. In parishes where the technology was not adopted, the riot probability was 13.6%; in places where threshing machines had spread, it was 26.1% - twice as high. Technology adoption may have been affected by the risk of riots. To identify the causal effect of new technology, we focus on soil composition. Early threshing machines only operated effectively with wheat. The presence of heavy soils – with a high proportion of clay – strongly predicts the cultivation of wheat. At the same time, they do not predict the share of land used for cereal farming in general, nor does it correlate with the composition of the workforce, population density, poor relief per capita, or the

[1]In the literature on the economic determinants of political conflict, the closest paper to ours is Autor et al. (2016)

gender ratio. Figure 1 documents the causal chain, with panel (a) showing the geographical distribution of riots in England, (b) of threshing machines by 1830, and (c) of heavy soils. As the zoomed-in area in panel (d) shows, Swing riots were much more frequent in areas with heavy soils. In other words, where farmers cultivated more wheat because their soil was more suitable for it, they bought more threshing machines, and there were more riots. This development was new – there is no effect of soil suitability on unrest before 1830.

Next, we examine factors that aggravated or reduced the incidence of riots. Workers whose livelihood was threatened by new technology had two choices: "voice" and "exit" (Hirschman, 1970); they could leave or engage in (violent) action. Parishes close to manufacturing centres saw fewer protests, suggesting that "exit" reduced protest frequency. In contrast, enclosure of common land exacerbated the effect of machines on riots.

Finally, we document important repercussions of the riots. In the most-affected areas, fewer labor-saving machines were adopted after 1832. In addition, patenting rates were reduced for decades where more Swing violence had occurred.

We contribute to two main literatures – one on labor markets effects of new technology, the other on the economic determinants of social unrest and civic conflict. A growing literature in labor-economics has demonstrated that the IT revolution has disadvantaged less educated workers (Acemoglu, 1998; Autor et al., 1998), because computers have replaced workers performing tasks that are easy to codify (Autor et al., 2003). More recently, robots are replacing workers, leading to lower wages (Acemoglu and Restrepo, 2018),[2] and there is also good evidence that new agricultural technologies can drive workers out of agriculture (Bustos et al., 2016).[3] However, what is unclear is whether such labor-saving technical change can create political instability and social unrest.

Much of the recent empirical literature on social unrest has focused on exogenous income shocks and their effects on conflict. Bohlken and Sergenti (2010) find that adverse weather shocks affecting income growth in India significantly predict Hindu-Muslim riots.[4] Brückner and Ciccone (2010) show that downturns in international prices of the main commodity exported by Sub-Saharan countries lead to higher chances of civil war.[5] Ponticelli and Voth

[2]During the Industrial Revolution, new technologies may have been more skill-replacing than skill-biased (James and Skinner, 1985; Mokyr, 1992). The direction of technical change itself may be endogenous to factor prices (Acemoglu, 2002; Acemoglu, 2007). This is in line with the early adoption of coal engines in England (Allen, 2009) and the introduction of new machines for treating non-U.S. cotton during the U.S. Civil War (Hanlon, 2015).

[3]In some cases, there is also a clear link from adverse labor market outcomes to political polarization (Autor et al., 2016).

[4]Miguel et al. (2004) present similar results for civil conflict in Africa.

[5]Bellemare (2014) examines related evidence for the whole world. Burke and Leigh (2010), Brückner

(2011) look at cross-country evidence for the period 1919 to 2008 and conclude that austerity has typically led to social turmoil. These results support the predictions of the model of Chassang and Padró i Miquel (2009) about the effects of temporary income shocks.

We also contribute to the historical literature on the 'Swing' riots. Systematic analysis began with the Parliamentary Inquiry that followed the unrest (Checkland, 1974). It largely blamed the riots on the Poor Law's failings. Hammond and Hammond (1920) famously attributed unrest to laborers' growing immiserization. Hobsbawm and Rudé (1969) argued that they were largely driven by the adverse effects of technological change. Stevenson (1979) emphasized that the riots were often aimed at Irish migrant workers, and not technology (see also Mokyr et al., 2015). Hobsbawn and Rudè's database was extended by Holland (2005). Aidt and Franck (2015) have recently argued that the riots facilitated passage of the 1832 Reform Act. Finally, Aidt et al. (2016) analyze how riots spread across England during the two years of unrest, and argue that 'contagion' played a significant role.

Relative to the existing literature, we make the following contributions: First, we unify the literatures on technological change and on the economic determinants of unrest, by providing evidence for an additional channel - the distributional effect of the new technology. The current literature on income and unrest overwhelmingly focuses on shocks that are negative overall. In contrast, new technologies represent a positive shock to output and productivity. Threshing machines are labor-saving, producing the same output with less work. This increased profits for landowners, but reduced the share of income going to labor.[6] Second, we focus on a massive, rapid dislocation in the labor market driven by technological change. Threshing was the main income source for agricultural laborers for many months of the year. Mechanical threshing largely eliminated winter earnings for agricultural laborers, who constituted the relative majority of the labor force in most English counties (Shaw-Taylor et al., 2010). This is in contrast with more recent cases of technological change, which involve relatively gradual shifts affecting a small part of the labor force (such as telephone operators or secretaries). Third, while threshing machines substituted unskilled workers, they did not create new occupations for skilled ones: manual threshers were replaced with equipment operated by horses, women and boys. This is in contrast with more recent cases

and Ciccone (2011) and Aidt and Leon (2016) argue that such economic downturns create a 'window of opportunity' that moves autocratic countries towards democracy.

[6]The importance of distributional effects of income shocks is central to the theory of Dal Bó and Dal Bó (2011). Dube and Vargas (2013) show evidence consistent with this theory looking at the conflict in Colombia. Berman et al. (2017) present results from African conflicts that speak to similar mechanisms. Other papers that have investigated the relationship between distribution and conflict are Esteban and Ray (1999), Esteban and Ray (2011), Mitra and Ray (2014) and Morelli and Rohner (2015).

of technology adoption, which often increase demand for high-skill jobs (Autor et al., 1998; Acemoglu and Restrepo, 2018).

1 Historical background

Threshing is a key agricultural activity. It loosens the grains from the husks (threshing), and then separates the husks from the grains (winnowing). Threshing is also a laborious process. Hand-threshing used flails swung overhead and provided winter employment, a time of the year when labor demand was low. In 1786, Andrew Meikle invented the first threshing machine (Macdonald, 1975). In this section, we describe English agriculture in 1800, and discuss the link between threshing machines and the 1830 riots.

1.1 Agriculture in early 1800 England

English agriculture by 1800 was highly commercialized. Estate owners often rented their land to farmers-tenants, who used advanced farming techniques (Hobsbawm and Rudé, 1969; Crafts, 1985; Overton, 1996; Allen, 1999; Rahm, 1844). Almost all output was sold on the market. By the 18$^{\text{th}}$ century, many agricultural laborers were hired by the day, the week, or the season (Thompson, 1963). During winter, many worked as threshers.[7] Clark (2001) estimates that prior to the introduction of threshing machines, threshing accounted for up to 50 percent of rural laborer's winter income. The Poor Laws made income support available to the poor:[8] Under this system, parishes had to support local residents seeking relief, but had no obligation towards outsiders (Marshall, 1977; Boyer, 1990). This discouraged migration even over short distances (Redford, 1976).[9]

Threshing machines spread slowly in the beginning because they were relatively expensive (Hobsbawm and Rudé, 1969; Macdonald, 1975). Productivity gains depended on the specific type of machine (Appendix B.3). Threshing machines operated by horses or water increased productivity by a factor of 5 and 10 respectively. Water power was often preferred.

[7] The Hammonds cite a landowner from Canterbury as saying that in his parish, "...where no machines had been introduced, there were twenty-three barns... in these barns fifteen men at least would find employment threshing corn up till May." (Hammond and Hammond, 1920).

[8] Elisabeth I introduced the Poor Law in 1601 with the "Acte for the Reliefe of the Poore" (Marshall, 1977). The basic framework remained in place until 1834 (Boyer, 1990, Clark and Page, 2008).

[9] Boyer (1990) argues that the Poor Law did not slow down aggregate rural-urban migration. His conclusion does not exclude the possibility that the Poor Laws prevented rural-rural migration, and Landau (1995) presents evidence that the "Laws of Settlement" systematically limited migration across parishes in the 18th century.

After 1810, threshing machines increasingly spread as their productivity and reliability grew. (Hobsbawm and Rudé, 1969).

1.2 Captain Swing riots

The first 'Swing' riots broke out in August 1830, in Kent.[10] They quickly spread across the country. More than 3,000 riots occurred across 45 counties. Almost all took place in rural areas, and all rioters were either rural workers or local craftsmen (Hobsbawm and Rudé, 1969; Stevenson, 1979). Arson attacks were common (Tilly, 1995); in many parishes rioters forced the overseers of the poor out. Between August and December 1830 alone, 514 threshing machines were attacked (Holland, 2005). Wage demands were also important; many farmers agreed to a minimum wage (Griffin, 2012; Hammond and Hammond, 1920).[11] Threatening letters – signed by the mythical 'Captain Swing' – were sent to farmers and by October 1830, *The Times* began to call the wave of riots 'Swing' (Griffin, 2012). Even though unrest simmered for over two years, most of the riots were over by April 1831 (see Figure B.3).[12]

After a slow response, the government adopted a hard line and ordered the army and local militias to quell the protests close to urban areas. It also set up a special commission which passed 252 death sentences (Hobsbawm and Rudé, 1969). In the end, the revival of labor demand in the spring of 1831 did much to reduce the incidence of protests.

Several factors contributed to the wave of riots in 1830-32. Hobsbawm and Rudé (1969) emphasize how bad weather, a poor harvest and the prospect of a cold winter aggravated the rural workers' situation. News of the French and Belgian revolutions may have contributed to initial unrest in Kent (Archer, 2000; Charlesworth, 1979). Domestic politics was tense too: discussions of electoral reform had come to naught under the Duke of Wellington's Tory government. Eventually, the Great Reform Act of 1832 would be passed – but only after Wellington's government fell during the peak of the riots (Aidt and Franck, 2015).

Rural workers' immiserization prepared the ground for unrest. Enclosures had deprived rural workers of access to common lands, effectively transforming them into a "landless proletarian, relying almost exclusively on wage-labor" (Hobsbawm and Rudé, 1969). Additionally,

[10] Hobsbawm and Rudé (1969) argue that 28$^{\text{th}}$ of August 1830 marked the start of the riots, when a gang of people smashed a threshing machine in Lower Hardres, Kent. Recently, Griffin (2012) demonstrated that riots began 4 days earlier, in Elham, Kent.

[11] Information on the type of unrest also allows us to look at another explanation for the Swing riots: resentment against tithes (Hobsbawm and Rudé, 1969). In our data, only 2 percent of the events are classified as "tithe riots": episodes during which workers demanded a reduction of tithes. We conclude that tithes were not central to the Swing riots.

[12] Hobsbawm and Rudé (1969); Hammond and Hammond (1920).

bringing in the harvest in cereal-producing areas required a large workforce – but employment opportunities were scarce during the rest of the year. The Poor Laws could sustain agricultural laborers year-round, but it came under growing strain as the population grew and cottage industries declined (Stevenson, 1979; Thompson, 1963).

The new threshing machines increasingly deprived rural laborers of their main source of income during the winter. Unemployment was on average 5.5 percent higher in winter than in summer. Where threshing machine had spread, this difference grew by an additional 2.1 percentage points.[13] While enclosures, Poor Laws and mechanization appear in almost any account of the Swing riots, there is so far no hard evidence to establish their causal effect.

2 Empirical analysis

This section presents our main empirical findings as well as our identification strategy.

2.1 Threshing machines and riots

To examine the association between threshing machines and riots, we estimate variants of

$$\text{Riots}_p = \beta_0 + \beta_1 \text{Machines}_p + \beta_2 \text{density}_p^{1801} + \beta_X X_p + \theta_r + e_p \tag{1}$$

where Riots_p is the number of unrest events in parish p during 1830-32, Machines_p is the number of threshing machines, density_p^{1801} is the (log of) population density in 1801, and X is a vector of additional controls including share of agricultural workers, male-female ratio, and distance to the closest newspaper town and to Elham, the village of the first riots. In the most demanding specification, we include θ_r, fixed effects for 4 regions of England plus Wales. Caird (1852) defines these regions pooling areas with very homogeneous agricultural systems.

Table 1 presents our main results. There is a strong and positive correlation between riots and adoption of the new machines. Coefficients are highly significant whether we control for parish characteristics (col. 1) or add region fixed effects (col. 2). Denser places and parishes with more skewed sex ratios had more riots, as did places closer to the first riot in Elham.[14]

[13] We combine data on threshing machine diffusion in 1800-1830 (described in Appendix A), with information on rural unemployment in 1834 (Checkland, 1974). Summer unemployment was essentially unaffected by machines ($\beta = -0.001$, $p = 0.868$). Table B.1 show that the positive association between threshing machines and winter unemployment survives the inclusion of controls.

[14] The number of Swing riots is a count variable and almost 86 percent of the parishes do not experience

The strength of the association is noteworthy because our measure of technology adoption is noisy, biasing our estimates downwards (Deaton, 1997). Unobservables are unlikely to drive our results – adding controls barely changes the size of the coefficient on threshing machines.[15] In Table B.2 we break down riots into two categories: attacks on threshing machines, and other type of revolt. We then estimate Equation (1) with these two measures. Col. 1-3 of Table B.2 report results for machine attacks and col. 4-6 for other types of unrest. That counties with more machines witnessed more attacks on threshers is not too surprising; importantly, these machines spelled higher probabilities for other types of unrest. For both variables, there is a robust correlation between machines and riots. This implies that threshing machines worked as a catalyst of general unrest: the more of them there were, the more protests occurred that were not directly aimed at the machines.

2.2 Identification

There are three reasons why OLS estimates may be biased. First, landlords and farmers may have been less inclined to adopt labor-saving technologies where the risk of protest was high. Anecdotal evidence from the period suggests that this is a valid concern.[16] This would bias estimates downwards. Second, there may be omitted variables that affect both the adoption of labor-saving technologies and the likelihood of rural protest. While the inclusion of observed characteristics does not affect point estimates in Table 1, it is still possible that other, unobserved characteristics correlate with technology adoption and riots. This could also affect our estimates. Third, measurement error in technology adoption is likely to bias coefficients downward, because we do not observe all threshing machines in use between 1800 and 1830.

To address these issues we need exogenous variation in the adoption of threshing machines. Grain suitability itself is not plausibly excludable, since it correlates with the number of workers in a parish – and without a sufficient number of dissatisfied individuals, there could be no riots. Our instrument is soil suitability *for wheat*. We expect it to predict thresher

unrest during 1830-32. Thus, a linear model may not be appropriate. Table C.1 in the appendix shows that results are robust to alternative estimation methods.

[15] If we compare the model on column 1 with the model that only controls for density , we find that selection of unobservables should be 54.8 percent of the selection on observable to rule out a significant effect of machines on riots (Altonji et al., 2005; Oster, 2017). This ratio is high, especially because unobservables include all threshing machines in operation in 1830 but not mentioned in newspapers or surveys.

[16] For instance Caird (1852) talks of an Oxfordshire farmer who, instead of using the plough, "had so many hands thrown upon him, that he resorted to spade husbandry, being the best means in which they could be employed."

adoption because wheat was the only grain suitable for mechanical threshing.[17] We measure wheat suitability with the share of land in a parish classified as consisting of "heavy soil", i.e. soil rich in clay. Due to the – somewhat unusual – characteristics of clay soils in Britain, the heavier the soil, the harder it was to cultivate wheat:

> "...clay... is fertile in proportion to the humus which it contains... It then forms ... rich wheat soils which produce many successive abundant crops... The clay soils of Britain are not in general of this fertile kind. They are of a compact nature which retains water; and the various oxides and salts of iron which they contain are mostly injurious to vegetation... This has made lighter soils, which are more easily worked, to be generally preferred... and the mode of cultivation of the light soils has advanced more rapidly towards perfection than that of the clays." (Rahm, 1844: entry on "clay".)

In other words, since wheat was the most valuable cash crop grown by farmers, it was more often sown on the lighter soils.

Table B.4 shows that land usage was in line with the expert assessment of soil suitability. It uses information on value and quantity of different crops sold in various market towns of England. Where the soil is heavy, wheat lost out to oats in the value of crops sold (col. 1-4). We find the same result if we look at the quantity of wheat sold, relative to oats (col. 5-8).

2.3 First stage: Threshing machines adoption

Figure 2, panel (a) documents the strength of the association between soil composition and threshing machine adoption. As the share of heavy soil increases from 0% to 100%, the penetration of threshing machines falls by half. Before proceeding further, we show that our sample is balanced with respect to the instrument. Figure 2 panel (b) shows that the share of heavy soils in a parish does not correlate with Poor Rates per capita, distance to Elham (where the first riots errupted), occupational composition, population density, the sex ratio, or the share of cereals grown. The same holds after controlling for wheat suitability (Table B.5, col. 2). Crucially, we find that our data is also balanced with respect to pre-1830 unrest. Panel (c) shows the effect of heavy soil on unrest over time. It is small and insignificant before 1830, and then becomes large. This suggests that threshing machines were not adopted to a greater extent in areas with a greater proclivity towards civic unrest.

[17] Hobsbawm and Rudé (1969) argue that "oats and barley were definitely cheaper to thresh by hand."

Next, we regress the number of threshing machines in parish p (Machines_p), on share of heavy soil in a parish

$$\text{Machines}_p = \alpha_0 + \alpha_1 \text{Share heavy}_p + \alpha_2 \text{density}_p^{1801} + \alpha_X X_p + \psi_r + u_p \tag{2}$$

The first stage is strong strong in all specifications. Columns 3-4 of Table 1 show the results. We obtain an F-statistic of 17.7 in the specification with controls, and of 15.9 when we add region fixed effects.

2.4 Reduced form and IV results

Before presenting our econometric results, we illustrate our findings. Figure 1 combines information on soil composition, threshing machine adoption, and the location of Swing riots. Panel (a) gives the distribution of riots. Panel (b) shows the spread of threshers by 1830, and panel (c) shows the distribution of heavy soils. Riots were concentrated in Wiltshire, Berkshire and Hampshire, in the South-Eastern counties of Kent and Sussex, and in Norfolk. These regions are also the ones that are more suitable to wheat cultivation, as indicated by their lower share of heavy soils. They are also the ones where threshers spread the most, and where unrest errupted with particular frequency in 1830.

The reduced form results point to a strong and robust relationship between our instrument and the incidence of riots. Figure 2, panel (d) shows the bivariate relationship. As the share of heavy soil increases from 0 to 100%, the likelihood of riots fall from over forty to less than 20 percent. When controlling for other factors, a higher share of heavy soil in a parish strongly predicts fewer riots (Table 1, columns 5-6).

The IV results are similar. Whether we use region fixed effects or not, we find that there is a large and significant effect from the part of machine adoption determined by soil composition on riot incidence. The IV estimates in Table 1 suggest that one extra machine, installed because of land characteristics, translated into 6.4-6.6 more riots during 1830-32. These numbers are significantly larger than OLS estimates. Because our measure of machines is noisy, measurement error can explain part of the difference.[18] We also interpret the discrepancy as a consequence of the different nature of these estimators. The IV estimator is a LATE and captures the causal effect of machines on riots in the subpopulation of compliers. This matters for two reasons. First, reverse causality is likely to attenuate OLS estimates, as

[18] To illustrate the severity of measurement error, consider that we observe direct attacks on threshers in 320 parishes. Only 36 of them (11 percent) had published advertisements mentioning these machines.

farmers scared of unruly workers were reluctant to install labor-saving machinery. This attenuation is not present in the IV, which is based on pre-existing geographical characteristics out of the control of farmers. Second, our instrument identifies the causal effect in a population of parishes where machines had the greatest impact on workers. Parishes that adopted machines because they were a good place to produce wheat were likely to be major wheat producers, providing summer employment to many rural workers. In these places, adoption of threshers was likely to create massive unemployment in winter, creating the conditions for unrest.

To illustrate the robustness of our results to limited violations of the exclusion restriction, we also perform the test proposed by Conley et al. (2012). We report these results in Figure B.4. The direct effect of the instrument on riots would have to account for between 74% and 78% of the overall effect before the estimated coefficient becomes insignificant. We consider such large direct effect of heavy soil on unrest unlikely.

Our OLS, reduced form, and IV results are robust to a wide range of alternative estimation methods, the inclusion of county fixed effects, and different corrections for spatial autocorrelation, as well as estimation for areas close to newspapers only: see Appendix C. The robustness of our results to the inclusion of county fixed effects is important: counties are small, relatively homogeneous geographical units. Because we find that threshers cause more riots even within these small areas, we conclude that unobservables are unlikely to drive our results.

3 Aggravating circumstances

What factors amplified or mitigated the impact of technology adoption on unrest? We document that in areas where other factors impoverished rural workers, the relationship between technology adoption and riots was stronger. In contrast, access to alternative employment dampened the effect of mechanization on riots.

3.1 Alternative employment

Where workers could easily find alternative employment, labor-saving technologies did not lead to social unrest - workers chose "exit" and not "voice" in the parlance of Hirschman (1970). In 1830s England, many towns were thriving. We expect rural workers living in areas nearby to migrate more readily in response to the introduction of labor-saving machines. In other words, in the presence of alternative urban employment opportunities, the introduction of threshing machines should engender less opposition, resulting in fewer Swing riots.

For each parish in England, we compute the distance to the closest manufacturing center. We split the sample into above-median and below-median distance from one of these 15 centers. The half that is closest to a manufacturing city will arguably have greater scope for rural-urban migration.[19]

We plot OLS estimates of Equation (1) for the two sub-samples in the left panel of Figure 3 (full results are in Table B.6). Solid black dots show that adoption of threshing machines was associated with significantly more riots in the 4,785 parishes that lie far away from manufacturing centers. The relationship is still significantly different from 0 for the other, closer half of the sample, but the coefficient is only one third in size. The coefficients are significantly different from each other in all specifications.

3.2 Enclosures

We now ask whether enclosure prior to 1820 amplified the effect of machine adoption on riots. This is plausible because enclosure on average worsened conditions for agricultural laborers, who had often kept cows or sheep on the commons (Neeson, 1996; Mingay, 2014). Where most land is enclosed, labor-saving technologies is especially harmful to workers since they have no other source of income.

In the right panel of Figure 3, we split our sample into two groups, by proportion of land enclosed (full results are in Table B.7).[20] The figure shows OLS regressions, with solid red dots for above-median enclosures, and open green ones for below-median parishes. In all cases, the relationship between machines and riots is strong and precisely estimated in parishes with above-median enclosures. In contrast, we find a markedly smaller effect in areas with few enclosures.

[19]The 15 manufacturing centers are in Cheshire, Lancashire, Middlesex, Norfolk, Warwickshire and Yorkshire, West Riding. See Appendix A.3 for details. The median parish is Waterstock in Oxfordshire, which lies 74 km from Blackburn.

[20]We only observe enclosures for registration districts, and parishes in the same district share the same value of enclosure. The median parish is in the districts of Biggleswade (Bedford), Billericay, Colchester, Ongar, Romford (Essex) and Market Harborough (Leicester). There are 107 parishes in these districts, and we assign them to the 'low' enclosure group: this is the reason why splitting parishes at the median does not produce two samples of exactly the same size.

4 Conclusions

Using newly-compiled data on the diffusion of threshing machines, we first demonstrate that during one famous historical episode, the 'Swing riots' in Britain in 1830-32, the geography of unrest was strongly correlated with the adoption of labor-saving technology. Where threshing machines had spread, the probability of riots was twice as high as in areas where they had not been adopted. We use soil suitability for wheat to identify an exogenous cause of treshing machine adoption – the machines were unsuitable for other crops. Areas with better conditions for wheat cultivation witnessed both greater adoption of threshing machines and markedly more riots. Importantly, soil suitability for wheat is uncorrelated with grain suitability overall. Areas most suited for wheat - and hence the adoption of threshing machines - also did not witness more social unrest prior 1830, reducing the risk of pretrends and unobservable factors driving our results. While many factors arguably contributed to the outbreak of unrest in England and Wales in 1830-32, we demonstrate a clear causal contribution of technological change to social unrest.

New technology did not spell more unrest to the same extent everywhere. In areas far away from major manufacturing towns, favorable conditions for threshing machine adoption had a particularly strong effect on arson, attacks on the local authorities, machine breaking, or tumultuous assemblies. In contrast, where ease of access to alternative employment made workers' exit a realistic option, technological unemployment was translated less into social unrest. The same pattern is visible for enclosures. Where workers had already lost access to common lands before 1830, reducing their income, threshing machine adoption was more likely to spill over into political instability.

Did the riots have repercussions after 1832? Hobsbawm (1952) argued that the Swing riots slowed the introduction of labor-saving technology thereafter: "The wrecking of the helpless farm-laborers in 1830 seems to have been the most effective of all. ... the thrashing machines did not return on anything like the old scale." Was technology adoption actually slowed down by the Swing riots?

To investigate the aftereffect of the riots, we look at technology adoption and the history of invention. Table 2 shows that areas affected by the riots saw a marked decline in technology adoption and the rate of innovation. We regress indicators for machine adoption and patenting on the distance to the closest machine broken during the Swing riots. For invention, we collect data on the place of residence of every inventor who registered a patent in Britain in the years 1813-1843 (Woodcroft, 1854). The results in Table 2, col. 1-4, show that places close to a machine-breaking riot were home to significantly fewer inventors in the

10 years after the riots.[21] The dependent variable is the number of inventors who registered a patent.[22] The negative effect of riots holds whether we control for previous inventive activity (col. 2), other parish characteristics (col. 3), or region fixed effects (col. 4). The final estimate in column 4 implies that a parish at an average distance from a riot (32 km) was home to a third more inventors than a parish where riots occurred.

Was the adoption of new machines also slower in areas with Swing riots?[23] We focus on the diffusion of threshing and mowing machines (which were also labor-saving and became available after 1832).[24] Table 2, col. 5-8 report the results. The dependent variable is the number of threshing machines and mowing machines observed in 1832-1853. The further away a parish is from the site of previous riots, the greater machine adoption was. When we add controls for past adoption (col. 6), parish characteristics (col. 7) and region fixed effects (col. 8), the coefficient remains large and significance improves. The effect is economically large: A parish at an average distance from a Swing riot adopted 42 percent more labor-saving machinery than an affected parish.

Social unrest as a result of technological unemployment has so far been a rare event – but such tranquility is not inevitable. The 'Swing' riots demonstrate that rapid, regionally concentrated job losses can quickly lead to political instability and violence. Importantly, such unrest can have effects that linger for decades, slowing technology adoption and reducing the rate of innovation.

[21] These results exclude 437 parishes within 10 km from one of the 15 manufacturing centers used in subsection 3.1. Inventors living in these parishes registered 71 percent of patents in the years 1813-1829 and 75 percent of patents in the years 1832-1843.

[22] This is a standard measure in this literature (Akcigit et al., 2018).

[23] Wheat-producing areas were more likely to adopt threshers prior to 1830 - which led to riots; they also had greater structural demand for them after 1830. We therefore restrict the sample to parishes within 35 km from a threshing machine attack during Swing. This focuses the analysis on the most important areas for cereal cultivation.

[24] We collect advertisements from 8 years: 1832, 1835, 1838, 1841, 1844, 1847, 1850 and 1853. Results with only threshing machine adoption are qualitatively similar. In all specifications we exclude urban areas and focus on rural parishes where riots were more likely to have had an impact.

References

Acemoglu, D. (1998): "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," *Quarterly Journal of Economics*, 113, 1055–1089.

——— (2002): "Directed Technical Change," *Review of Economic Studies*, 69, 781–809.

——— (2007): "Equilibrium Bias of Technology," *Econometrica*, 75, 1371–1409.

Acemoglu, D. and D. Autor (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," in *Handbook of Labor Economics*, Elsevier, vol. 4, 1043–1171.

Acemoglu, D. and P. Restrepo (2018): "Robots and Jobs: Evidence from US Labor Markets," *NBER* 23285.

Aidt, T. S. and R. Franck (2015): "Democratization Under the Threat of Revolution: Evidence From the Great Reform Act of 1832," *Econometrica*, 83, 505–547.

Aidt, T. S. and G. Leon (2016): "The Democratic Window of Opportunity: Evidence from Riots in Sub-Saharan Africa," *Journal of Conflict Resolution*, 60, 694–717.

Aidt, T. S., G. Leon, and M. Satchell (2016): "The Social Dynamics of Riots: Evidence from the Captain Swing Riots 1830-1831," *Working Paper*.

Akcigit, U., J. Grigsby, T. Nicholas, and S. Stantcheva (2018): "Taxation and Innovation in the 20th Century," *NBER* 24982.

Allen, R. C. (1999): "Tracking the Agricultural Revolution in England," *Economic History Review*, 209–235.

——— (2009): *The British Industrial Revolution in Global Perspective*, New York: Cambridge Univ. Press.

Altonji, J. G., T. E. Elder, and C. R. Taber (2005): "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy*, 113, 151–184.

Archer, J. E. (2000): *Social Unrest and Popular Protest in England, 1780-1840*, Cambridge, UK: Cambridge Univ. Press.

Autor, D. H., D. Dorn, G. Hanson, and K. Majlesi (2016): "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure," *NBER* 22637.

Autor, D. H., L. F. Katz, and A. B. Krueger (1998): "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, 113, 1169–1213.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118, 1279–1333.

Batchelor, T. (1813): *General View of the Agriculture of the County of Bedford: Drawn Up for the Consideration of the Board of Agriculture and Internal Improvement*, Sherwood, Neely and Jones.

Bellemare, M. F. (2014): "Rising Food Prices, Food Price Volatility, and Social Unrest," *American Journal of Agricultural Economics*, 97, 1–21.

Berman, N., M. Couttenier, D. Rohner, and M. Thoenig (2017): "This Mine is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review*, 107, 1564–1610.

Bohlken, A. T. and E. J. Sergenti (2010): "Economic Growth and Ethnic Violence: An Empirical Investigation of Hindu–Muslim Riots in India," *Journal of Peace Research*, 47, 589–600.

Boyer, G. R. (1990): *An Economic History of the English Poor Law 1750—1850*, Cambridge, UK: Cambridge Univ. Press.

British Library and Findmypast (2016): "The British Newspaper Archive," .

Brückner, M. and A. Ciccone (2010): "International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa," *Economic Journal*, 120, 519–534.

——— (2011): "Rain and the Democratic Window of Opportunity," *Econometrica*, 79, 923–947.

Brunt, L. and E. Cannon (2013): "The Truth, the Whole Truth, and Nothing but the Truth: The English Corn Returns as a Data Source in Economic History, 1770–1914," *European Review of Economic History*, 17, 318–339.

Burke, P. J. and A. Leigh (2010): "Do Output Contractions Trigger Democratic Change?" *American Economic Journal: Macroeconomics*, 2, 124–157.

Bustos, P., B. Caprettini, and J. Ponticelli (2016): "Agricultural Productivity and Structural Transformation: Evidence from Brazil," *American Economic Review*, 106, 1320–1365.

Caird, S. J. (1852): *English Agriculture in 1850-51*, Longman, Brown, Green, and Longmans.

Charlesworth, A. (1979): *Social Protest in a Rural Society: The Spatial Diffusion of the Captain Swing Disturbances of 1830-1831*, Norwich: Historical Geography Research.

Chassang, S. and G. Padró i Miquel (2009): "Economic Shocks and Civil War," *Quarterly Journal of Political Science*, 4, 211–228.

Checkland, S. G. (1974): *The Poor Law Report of 1834*, London: Penguin Books.

Clark, G. (1987): "Productivity Growth Without Technical Change in European Agriculture Before 1850," *Journal of Economic History*, 47, 419–432.

——— (2001): "Farm Wages and Living Standards in the Industrial Revolution: England, 1670—1869," *Economic History Review*, 54, 477–505.

Clark, G. and M. Page (2008): "Welfare Reform, 1834," *Working Paper*.

Colella, F., R. Lalive, S. O. Sakalli, and M. Thoenig (2019): "Inference with Arbitrary Clustering," *Working Paper*.

Conley, T. (1999): "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics*, 92, 1–45.

Conley, T. G., C. B. Hansen, and P. E. Rossi (2012): "Plausibly Exogenous," *Review of Economics and Statistics*, 94, 260–272.

Crafts, N. F. (1985): *British Economic Growth During the Industrial Revolution.*, Oxford: Oxford Univ. Press.

Dal Bó, E. and P. Dal Bó (2011): "Workers, Warriors, and Criminals: Social Conflict in General Equilibrium," *Journal of the European Economic Association*, 9, 646–677.

Deaton, A. (1997): *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*, Baltimore: John Hopkins Univ. Press.

Donaldson, J. (1794): *General View of the Agriculture of the County of Banff*, Thomas Ruddiman.

Dube, O. and J. F. Vargas (2013): "Commodity Price Shocks and Civil Conflict: Evidence from Colombia," *Review of Economic Studies*, 80, 1384–1421.

Esteban, J. and D. Ray (1999): "Conflict and Distribution," *Journal of Economic Theory*, 87, 379–415.

——— (2011): "Linking Conflict to Inequality and Polarization," *American Economic Review*, 101, 1345–1374.

Gonner, E. C. K. (1912): *Common Land and Inclosure*, MacMilland and Co.

Griffin, C. J. (2012): *The Rural War: Captain Swing and the Politics of Protest*, Manchester: Manchester Univ. Press.

Hammond, J. L. and B. Hammond (1920): *The Village Labourer, 1760 - 1832: A Study in the Government of England Before the Reform Bill*, Sutton.

Hanlon, W. W. (2015): "Necessity Is the Mother of Invention: Input Supplies and Directed Technical Change: Directed Technical Change," *Econometrica*, 83, 67–100.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones, and A. Jarvis (2005): "Very high resolution interpolated climate surfaces for global land areas," *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 25, 1965–1978.

Hirschman, A. O. (1970): *Exit, Voice, and Loyalty: Responses to Decline in Firms, Organizations, and States*, Cambridge, Mass: Harvard Univ. Press.

Hobsbawm, E. J. (1952): "The Machine Breakers," *Past & Present*, 1, 57–70.

Hobsbawm, E. J. and G. F. E. Rudé (1969): *Captain Swing*, London: Verso.

Holland, M. (2005): *Swing Unmasked: The Agricultural Riots of 1830 to 1832 and Their Wider Implications*, Milton Keynes: Family and Community Historical Research Society Publishing.

James, J. A. and J. S. Skinner (1985): "The Resolution of the Labor-Scarcity Paradox," *Journal of Economic History*, 45, 513–540.

KAIN, R. J. AND R. R. OLIVER (2001): *The Historic Parishes of England and Wales: An Electronic Map of Boundaries Before 1850 with a Gazetteer and Metadata*, Twayne Publishers.

KEYNES, J. M. (1931): "Economic Possibilities for our Grandchildren," in *Essays in Persuasion*, New York: Palgrave Macmillan, 321–332.

LANDAU, N. (1995): "Who Was Subjected to the Laws of Settlement? Procedure under the Settlement Laws in Eighteenth-Century England," *Agricultural History Review*, 43, 139–159.

LAWLEY, R. (2009a): *The Soil-Parent Material Database: Methodology*, Nottingham, UK: British Geological Survey.

——— (2009b): *User Guide: Soil-Parent Material 1 Kilometre Dataset*, Nottingham, UK: British Geological Survey.

LEONTIEF, W. (1952): "Machines and Man," *Scientific American*, 187, 150–160.

LUTERBACHER, J., D. DIETRICH, E. XOPLAKI, M. GROSJEAN, AND H. WANNER (2004): "European Seasonal and Annual Temperature Variability, Trends, and Extremes Since 1500," *Science*, 303, 1499–1503.

MACDONALD, S. (1975): "The Progress of the Early Threshing Machine," *Agricultural History Review*, 23, 63–77.

MARSHALL, J. D. (1977): *The Old Poor Law: 1795 - 1834*, London: Macmillan.

MARX, K. (1867): *Capital: A Critique of Political Economy*, London: Penguin Books.

MAVOR, W. F. (1813): *General View of the Agriculture of Berkshire*, Sheerwood, Neely and Jones.

MIGUEL, E., S. SATYANATH, AND E. SERGENTI (2004): "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy*, 112, 725–753.

MINGAY, G. E. (2014): *Parliamentary Enclosure in England: An Introduction to its Causes, Incidence and Impact, 1750-1850*, London: Routledge.

MITRA, A. AND D. RAY (2014): "Implications of an Economic Theory of Conflict: Hindu-Muslim Violence in India," *Journal of Political Economy*, 122, 719–765.

MOKYR, J. (1992): *The Lever of Riches: Technological Creativity and Economic Progress*, New York: Oxford Univ. Press.

MOKYR, J., C. VICKERS, AND N. L. ZIEBARTH (2015): "The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?" *Journal of Economic Perspectives*, 29, 31–50.

MORELLI, M. AND D. ROHNER (2015): "Resource Concentration and Civil Wars," *Journal of Development Economics*, 117, 32–47.

MOULTON, B. R. (1990): "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units," *Review of Economics and Statistics*, 72, 334–338.

Neeson, J. M. (1996): *Commoners: Common Right, Enclosure and Social Change in England, 1700 - 1820*, Cambridge, UK: Cambridge Univ. Press.

Oster, E. (2017): "Unobservable Selection and Coefficient Stability: Theory and Evidence," *Journal of Business & Economic Statistics*, 37, 1–18.

Overton, M. (1996): *Agricultural Revolution in England: The Transformation of the Agrarian Economy 1500-1850*, Cambridge, UK: Cambridge Univ. Press.

Pauling, A., J. Luterbacher, C. Casty, and H. Wanner (2006): "Five Hundred Years of Gridded High-Resolution Precipitation Reconstructions Over Europe and the Connection to Large-Scale Circulation," *Climate Dynamics*, 26, 387–405.

Ponticelli, J. and H.-J. Voth (2011): "Austerity and Anarchy: Budget Cuts and Social Unrest in Europe, 1919-2008," *Working Paper.*

Rahm, W. L. (1844): *Dictionary of the Farm*, London: Charles Knight and Co.

Redford, A. (1976): *Labour Migration in England, 1800-1850*, Manchester: Manchester Univ. Press.

Shaw-Taylor, L., R. S. Davies, P. M. Kitson, G. Newton, A. E. M. Satchell, and E. A. Wrigley (2010): "The Occupational Structure of England and Wales c. 1817-1881," *Working Paper.*

Southall, H. and N. Burton (2004): *GIS of the Ancient Parishes of England and Wales, 1500-1850*, Colchester, Essex: UK Data Archive.

Southall, H., P. Ell, D. A. Gatley, and I. Gregory (2004): *Great Britain Historical Database: Census Data: Parish-Level Population Statistics, 1801-1951*, Colchester, Essex: UK Data Archive.

Stevenson, J. (1979): *Popular Disturbances in England, 1700-1832*, London: Longman.

Thompson, E. P. (1963): *The Making of the English Working Class*, London: Penguin Books.

Tilly, C. (1995): *Popular Contention in Great Britain, 1758-1834*, Cambridge, Mass: Harvard Univ. Press.

Turner, M. E. (1982): "Agricultural Productivity in England in the Eighteenth Century: Evidence From Crop Yields," *Economic History Review*, 35, 489–510.

——— (2005): *Crop Returns for England, 1801*, UK Data Service.

Wigton-Jones, E. (2019): "Legacies of Inequality: The Case of Brazil," *Working Paper.*

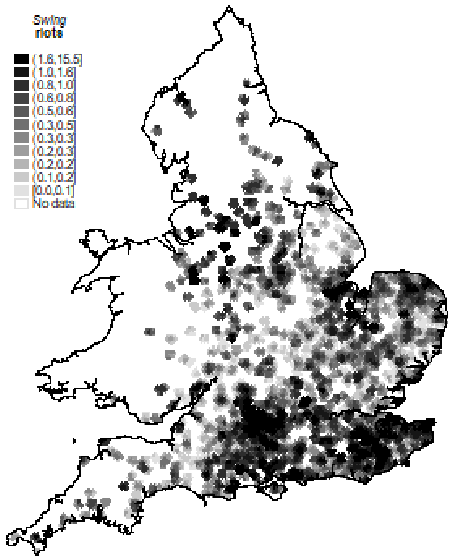
Woodcroft, B. (1854): *Titles of Patents of Invention: Chronologically Arranged from March 2, 1617 (14 James I.) to October 1, 1852 (16 Victoriæ)*, London, UK: Queen's Printing Office.

Xoplaki, E., J. Luterbacher, H. Paeth, D. Dietrich, N. Steiner, M. Grosjean, and H. Wanner (2005): "European Spring and Autumn Temperature Variability and Change of Extremes Over the Last Half Millennium," *Geophysical Research Letters*, 32.

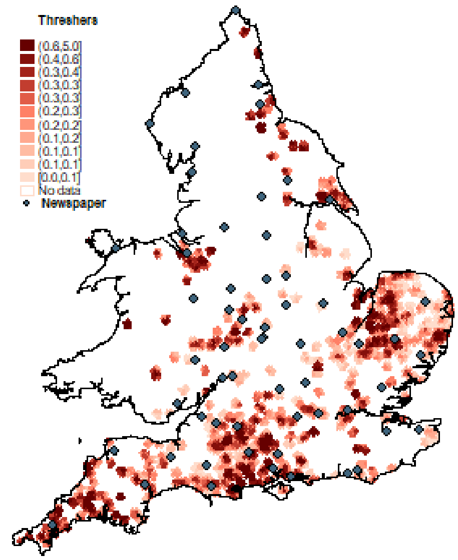
Figures

Figure 1: Swing riots, threshers and soil composition

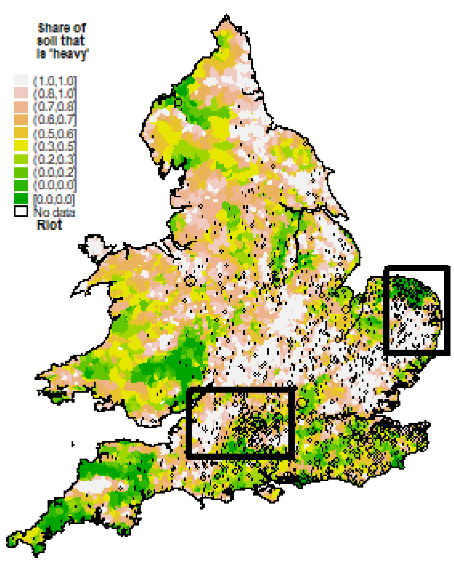
(a) *Swing* riots



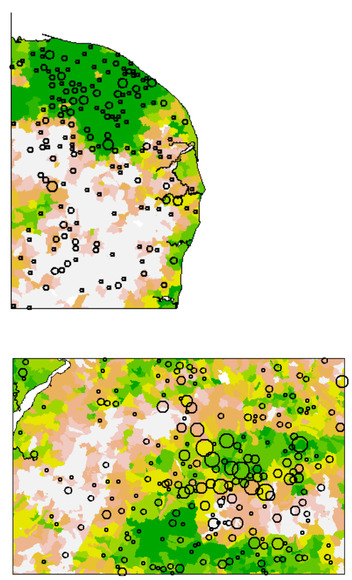
(b) Threshers



(c) Soil composition

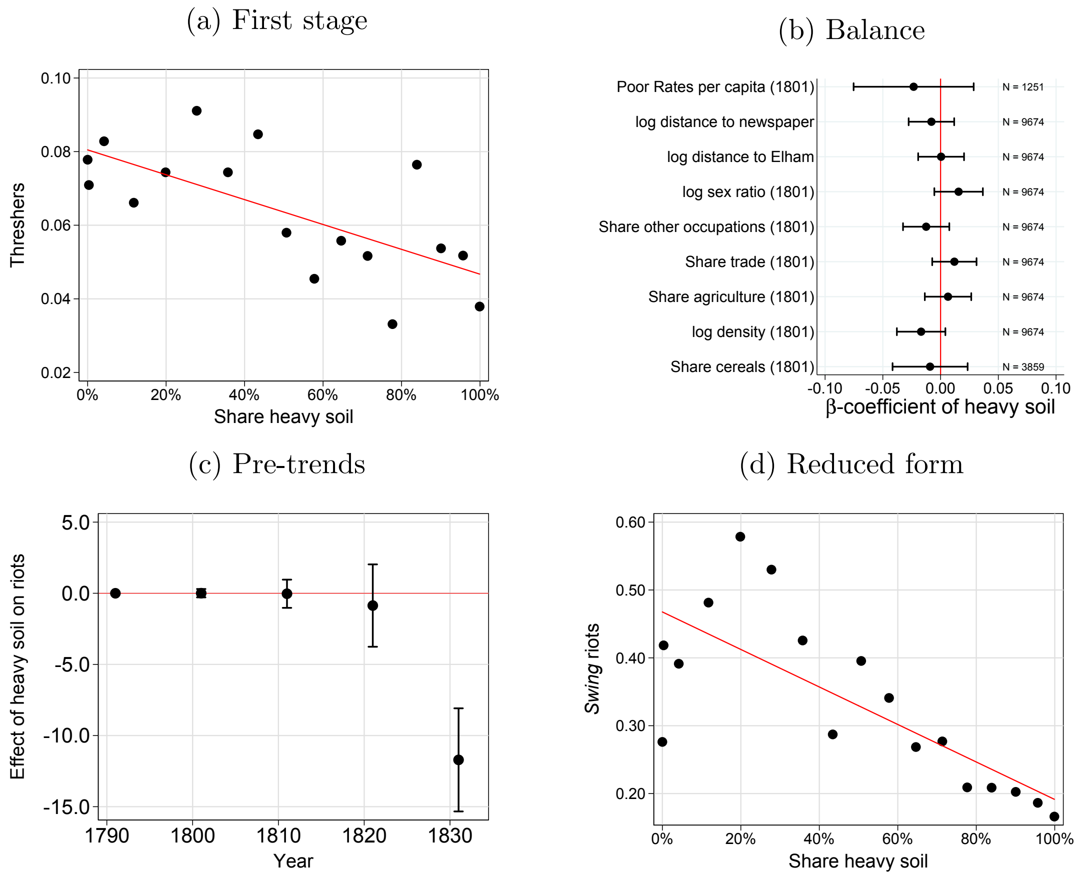


(d) Hotspots of *Swing*



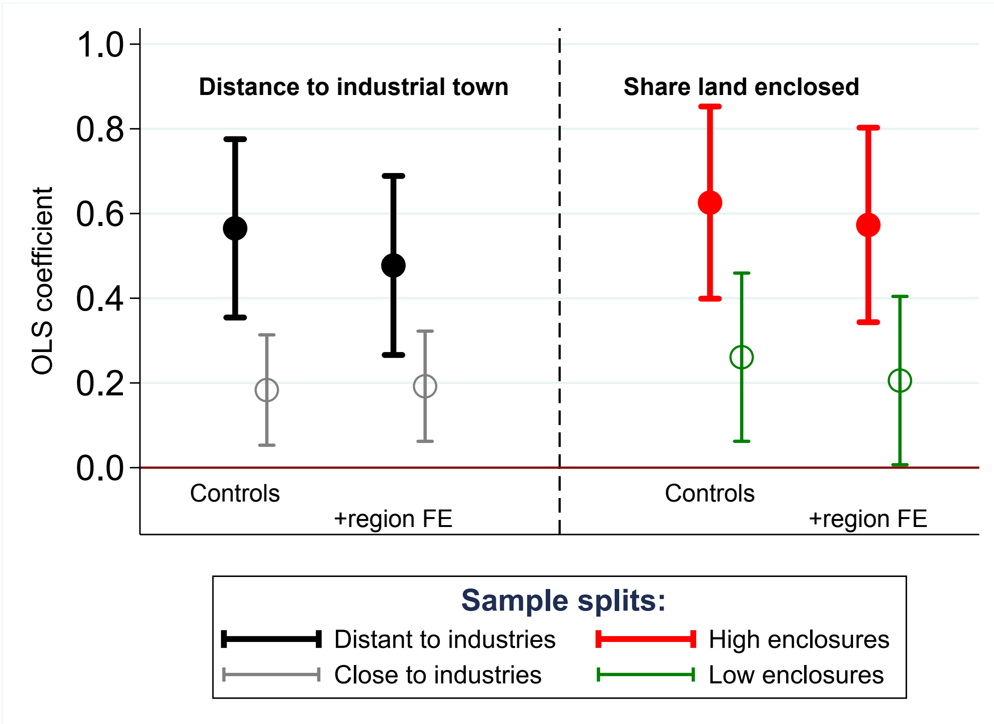
Notes: Panel (a): distribution of Swing riots from Holland (2005). We plot a uniform spatial kernel with bandwidth 5km. Panel (b): distribution of threshers from British Library and Findmypast (2016) and *General Views of Agriculture*. We plot a uniform spatial kernel with bandwidth 5km. Panel (c): share of parish area that is heavy from Lawley (2009b). Panel (d): heavy soils and riots in North Anglia (top) and South England (bottom).

Figure 2: Validity of the instrument: first stage, balance, pre-trends, and reduced form.



Notes: Panel (a): first stage. Share of heavy soils (x-axis) against number of threshers (y-axis). Panel (b): balance of share of heavy soil relative to observable parish characteristics: the graph plots beta coefficients of bi-variate regressions of the variables listed on the left on the share of heavy soil. See Table B.5, col. 1 for actual coefficients. Panel (c): relationship between pre-1830 riots and share of heavy soils (see Table B.3, col. 4 for full estimates). Panel (d): reduced form. Share of heavy soil (x-axis) against number of Swing riots (y-axis).

Figure 3: Aggravating circumstances



Notes: Aggravating circumstances. The figure reports point estimates and 95 percent confidence intervals for the main specifications estimated on different sample splits. Left panel: parishes distant from (close to) industries are above (below) the median distance from one of the 15 manufacturing centers of England (see Appendix A.3 for details). See Table B.6 for full results. Right panel: parishes with high (low) enclosures are above (below) the median level of enclosure (see Appendix A.3 for details). See Table B.7 for full results.

Tables

Table 1: Main results.

No. of	Swing riots		threshers		Swing riots			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
No. of threshers	0.389	0.353					6.361	6.557
	[0.071]	[0.071]					[1.616]	[1.768]
Share of area in parish whose soil is heavy			-0.034	-0.033	-0.218	-0.214		
			[0.008]	[0.008]	[0.026]	[0.027]		
Cereal suitability index			0.050	0.044	0.130	0.290	-0.186	0.001
			[0.032]	[0.032]	[0.092]	[0.096]	[0.242]	[0.245]
log 1801 density	0.101	0.099	0.015	0.013	0.103	0.100	0.011	0.013
	[0.018]	[0.018]	[0.004]	[0.004]	[0.018]	[0.018]	[0.034]	[0.034]
Share of agricultural workers in 1801	-0.065	-0.056	-0.015	-0.022	-0.073	-0.064	0.024	0.081
	[0.044]	[0.043]	[0.010]	[0.010]	[0.045]	[0.044]	[0.079]	[0.087]
log 1801 sex ratio	-0.181	-0.193	-0.024	-0.011	-0.187	-0.203	-0.035	-0.130
	[0.042]	[0.043]	[0.014]	[0.014]	[0.043]	[0.044]	[0.101]	[0.099]
log distance to Elham	-0.325	-0.217	-0.006	0.070	-0.335	-0.217	-0.294	-0.674
	[0.029]	[0.045]	[0.004]	[0.007]	[0.031]	[0.047]	[0.040]	[0.133]
log distance to newspaper	0.022	0.019	-0.000	-0.000	0.022	0.022	0.025	0.022
	[0.018]	[0.019]	[0.005]	[0.006]	[0.018]	[0.019]	[0.036]	[0.041]
Constant	1.600	1.014	0.036	-0.399	1.701	0.982	1.472	3.596
	[0.153]	[0.251]	[0.032]	[0.045]	[0.154]	[0.252]	[0.242]	[0.811]
Region fixed effects (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.057	0.064	0.006	0.032	0.052	0.061		
Mean dependent variable	0.308	0.308	0.062	0.062	0.308	0.308	0.308	0.308
F-test excluded instrument			17.7	15.9				
Rubin-Anderson test (p)							0.000	0.000
Observations	9674	9674	9674	9674	9674	9674	9674	9674

Notes: Col. 1-2: OLS estimates of Equation (1); dependent variable is number of Swing riots. Col. 3-4: first stage estimates of Equation (2); dependent variable is number of threshers. Col. 5-6: reduced form estimates; dependent variable is number of Swing riots. Col. 7-8: IV estimates of Equation (1), using share of heavy soil as instrument; dependent variable is number of Swing riots. See Table C.3 for results with county fixed effects. Robust standard errors in brackets.

Table 2: Aftermath: Effect of riots on innovation and technology adoption.

No. of	Patents after Swing				Threshers & mowers after Swing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance to machine attack	0.386	0.281	0.569	0.480	0.999	1.208	1.747	1.894
	[0.214]	[0.138]	[0.184]	[0.208]	[0.531]	[0.527]	[0.584]	[0.565]
No. of patents in parish 1813-29		0.802	0.781	0.780				
		[0.128]	[0.129]	[0.129]				
No. of threshers 1800-29						0.101	0.097	0.087
						[0.032]	[0.031]	[0.032]
log 1801 density			0.034	0.035			0.026	0.027
			[0.009]	[0.009]			[0.008]	[0.008]
Share of agricultural workers in 1801			-0.012	-0.010			-0.009	-0.013
			[0.009]	[0.009]			[0.018]	[0.018]
log 1801 sex ratio			0.002	-0.002			-0.039	-0.045
			[0.015]	[0.015]			[0.020]	[0.022]
log distance to Elham			-0.003	-0.003			-0.015	0.005
			[0.006]	[0.006]			[0.007]	[0.008]
log distance to newspaper			-0.026	-0.027			-0.026	-0.029
			[0.012]	[0.013]			[0.015]	[0.015]
Constant	0.028	0.006	-0.030	-0.028	0.047	0.037	0.088	-0.008
	[0.006]	[0.006]	[0.044]	[0.046]	[0.008]	[0.008]	[0.061]	[0.065]
Region fixed effects (5)	No	No	No	Yes	No	No	No	Yes
R^2	0.001	0.423	0.430	0.430	0.000	0.006	0.012	0.023
Mean dependent variable	0.040	0.040	0.040	0.040	0.061	0.061	0.061	0.061
Observations	9306	9306	9306	9306	6500	6500	6500	6500

Standard errors in brackets

Notes: Col. 1-4: dependent variable is number of patent whose inventor resided in the parish: 1832-43. Col 5-8: dependent variable is number of threshers and mowing machines: 1832-53. Robust standard errors in brackets.

Appendices (for online publication)

A Data appendix

A.1 Sources

We combine data on the Swing riots with hand-collected data on threshing machine adoption during the period 1800-30 as well as on pre-1830 riots. In addition, we use information from the 1801 crop returns, the 1801 British Census and the 1832 Poor Law Commission Report. Finally, we use modern-day data on local geographic and soil conditions. Here, we describe each of these sources (variable construction is in Appendix A.3).

The Family and Community Historical Research Society compiled detailed data on the Swing riots (Holland, 2005).[25] The main underlying source are judicial records; in addition, they use newspaper accounts of the time. The database contains date, parish, and type of crime perpetrated by rioters.[26] Figure 1 panel (a) shows the geographical distribution of these incidents. Figure B.3 reports the total number of Swing riots over time, differentiating between attacks on threshing machines and the rest.

Two separate sources provide information on threshing machine adoption. The first are advertisements from 60 regional newspapers. The second are the *General Views of Agriculture*, a collection of surveys analyzing English agriculture between 1790 and 1820. Some 118,758 newspaper issues were published between January 1800 and July 1830. We search them for the exact string 'threshing machine'. The ads we find either announce that a farm with a threshing machine is available for lease or sale, or that a manufacturer of threshing machines invites interested farmers to see them at work at one of their customers in the vicinity (see Figure B.1 and B.2 for examples). From 549 advertisements, we find evidence of adoption in 466 parishes.

We complement this list with information from the *General Views of Agriculture*. These surveys were sponsored by the Board of Agriculture. Each volume covers a single county. The first surveys appeared in the 1790s and were followed by second editions during the 1810s. There are few references to threshing machines in the early editions. By 1810, however, threshing machines were so widespread that each volume devotes an entire chapter to them. Surveyors discuss technical characteristics, including productivity, and provide information on the owner and location of the machine. Figure 1 panel (b) shows the geographical distribution of threshing machines.

To explain threshing machines adoption, we use information on soil composition from from the British Geological Survey (Lawley, 2009a,b). Figure 1 panel (c) presents a map of England and Wales, showing the share of heavy soils. It varies from zero to 100%, often within small geographical units. While some broad geographical patterns are apparent, each county of the UK contains a wide variety of soil types. The data comes from the 2007 Geological

[25] Aidt and Franck (2015) use the same data in their study of the political consequences of Swing riots.

[26] Holland (2005) builds on Hobsbawm and Rudé (1969), adding a further 1642 riots to their original list of 1475 incidents.

Map of Great Britain and records for each cell of a 1×1 km raster the parent soil material. The parent soil material is the first geological deposit underneath top soils: it determines the characteristics of top soils, including texture, chemistry and drainage (Lawley, 2009a). While human use of the land can modify soil composition slowly and at the margin, it is unlikely to have changed the parent soil material between the first half of 1800s, the date of our study, and the 20$^{\text{th}}$ century.

In addition, we use the 1801 British population census (Southall et al., 2004) to reconstruct demographic and sectoral composition of each parish, data from market towns on the share of crops sold in the 1830s (Brunt and Cannon, 2013), the 1801 corn returns (Turner, 1982), the tables in Gonner (1912) to measure enclosures before 1800, and the data in Luterbacher et al. (2004) and Pauling et al. (2006) for historical weather data. Finally, we calculate distances using parish centroids, based on an 1851 map of parishes (Southall and Burton, 2004). Table A.1 reports summary statistics for our variables and Appendix A.3 details variable construction.

Table A.1: Summary statistics

		Mean	St. dev.	Obs.
Unrest	Riots before Swing (1758-1829)	0.067	0.687	9674
	Swing riots (1830-32)	0.308	1.107	9674
	Attacks on machines during Swing (1830-32)	0.053	0.367	9674
Technology	Threshing machines before Swing (1800-29)	0.062	0.289	9674
	Threshing and mowing machines after Swing (1832-53)	0.054	0.377	9674
	Patents before Swing (1813-28)	0.077	1.028	9674
	Patents after Swing (1832-43)	0.111	1.482	9674
Population	Density (1801)	248.5	2855	9674
	Share of agricultural workers (1801)	0.386	0.265	9674
	Share of trade workers (1801)	0.117	0.142	9674
	Share of other workers (1801)	0.497	0.273	9674
	Sex ratio (1801)	0.994	0.293	9674
Agriculture	Share of land cultivated with cereal (1801)	0.837	0.119	3859
	Wheat oat value sold ratio (1820s)	71.75	370.4	9562
	Wheat oat quantity sold ratio (1820s)	24.81	129.9	9562
Geography	Distance to Elham (first riot - km)	237.1	108.2	9674
	Distance to closest town with newspaper (km)	24.22	17.79	9674
	Distance to closest industrial town (km)	88.56	63.35	9674
	Share of heavy soil	0.517	0.364	9674
Weather	Cereals suitability index	0.634	0.097	9674
	Abnormal precipitation (spring 1830 - mm)	18.76	15.76	9674
	Abnormal precipitation (summer 1830 - mm)	104.1	22.66	9674
	Abnormal temperature (fall 1830 - degrees)	0.277	0.068	9674
Other	Share of land enclosed (1800)	3.032	4.355	6715
	Poor Rates per capita (1801)	0.695	0.422	1251
	Unemployment share (winter 1834)	0.128	0.151	595
	Unemployment share (summer 1834)	0.067	0.112	613
	Unemployment share (winter - summer 1834)	0.055	0.101	574

A.2 Ancient parishes of England and Wales

To construct our database, we start from the map of ancient parishes of England and Wales prepared by Southall and Burton (2004). This map derives from earlier electronic maps by Kain and Oliver (2001), and contains a GIS database of all parishes of England and Wales in 1851. The map consists of 22,729 separate polygons, each identifying a separate place in England and Wales. These places are localities smaller than a parish, so that a given parish is often made of several distinct places. Because we observe all our variables at the parish level, we start by aggregating the 22,729 polygons into 11,285 parishes.[27] Next, we aggregate a subset of these parishes into larger units of observation. We do this in two cases. First, large urban areas such as London, Liverpool or Manchester consists of several distinct parishes. Treating these areas as separate observations is incorrect, because we always observe riots and threshing machines for a whole city, and we are never able to assign them to any specific area within the city. Thus, we assign all parishes belonging to a city to a single observation. We also aggregate different parishes into larger units when the information from at least one of our sources does not allow us to compute one of our variables more precisely. This happens when one of our sources records a riot, a threshing machine or Census population for a large area comprising several parishes. In these cases, we also aggregate all variables at the level of the larger unit of observation. Table A.2 reports the full list of towns constructed aggregating more than one parish.[28] At the end of this process, we are left with 10,700 separate observations. Of these, we are able to match 9,737 to the 1801 Population Census based on county and parish name. We drop 59 observations that report 0 workers and 1 that reports 0 men.[29] Finally the area of 2 parishes was so small that we could not evaluate the suitability of the soil from the geographical raster: we drop these parishes too. The final sample consists of 9,764 observations.

[27] We do this based on the fields GAZ_CNTY and PAR, which identify county and parish.

[28] There is a second reason for aggregating parishes within cities. Because most of riots and almost all machines appear in rural areas, keeping separate observations for each urban parish effectively duplicates observations with no riots and no machines. This would introduce the "Moulton problem" (Moulton, 1990) and, by biasing standard errors downwards, it would artificially increase the precision of our estimates.

[29] These 0s create missings in the share of agricultural workers and in the log sex ratio.

Table A.2: List of cities and towns created by aggregating more than one parish.

County	City or village	Parishes aggregated
London	London	80
Yorkshire, West Riding	York	55
Norfolk	Norwich	36
Devon	Exeter	25
Kent	Canterbury	24
Lincolnshire	Lincoln	21
Gloucestershire	Bristol	20
Oxfordshire	Oxford	13
Cheshire	Chester	13
Suffolk	Ipswich	13
Hampshire	Winchester	12
Gloucestershire	Gloucester	12
Essex	Colchester	12
Cambridgeshire	Cambridge	12
Leicestershire	Leicester	11
Worcestershire	Worcester	11
Sussex	Chichester	11
Sussex	Hastings	7
Shropshire	Shrewsbury	7
Hampshire	Southampton	7
Sussex	Lewes	6
Herefordshire	Hereford	6
Lincolnshire	Stamford	5
Surrey	Guildford	5
Bedfordshire	Bedford	5
Northamptonshire	Northampton	5
Berkshire	Wallingford	5
Yorkshire, East Riding	Beverley	4
Brecknockshire	Brecon	4
Derbyshire	Derby	4
Cambridgeshire	Ely	4
Huntingdonshire	Huntingdon	4
Norfolk	Lynn	4
Wiltshire	Salisbury	4
Kent	Sandwich	4
Suffolk	Sudbury	4
Yorkshire, North Riding	Thornton Dale and Ellerburn	4
Middlesex	Westminster	4
Norfolk	Wiggenhall St German	4
Somerset	Bath	3
Norfolk	Bircham	3
Dorset	Blandford	3
Buckinghamshire	Brickhill	3
Glamorganshire	Cardiff	3
Kent	Dover	3
Worcestershire	Droitwich	3
Suffolk	Fornham	3
Hertfordshire	Hertford	3
Essex	Maldon	3
Nottinghamshire	Nottingham	3
Berkshire	Reading	3
Kent	Rochester	3
Lincolnshire	Saltfleetby	3
Huntingdonshire	Sawtry	3
Dorset	Shaftesbury	3
Lincolnshire	Wainfleet	3
Dorset	Wareham	3
Berkshire	Windsor	3
Berkshire	Abingdon	2
Cambridgeshire	Abington	2
Norfolk	Alpington and Yelverton	2
Hampshire	Alresford	2
Devon	Axminster and Uplyme	2
Kent	Barming	2
Oxfordshire	Barton	2
Norfolk	Bawburgh and Bowthorpe	2
Norfolk	Beckham	2
Norfolk	Beechamwell	2
Norfolk	Beeston and Bittering	2
Sussex	Bersted and Pagham	2
Northamptonshire	Boddington	2
Somerset	Brewham	2
Berkshire	Bucklebury Stanford	2
Suffolk	Bungay	2
Suffolk	Bury St Edmunds	2
Cumberland	Carlisle	2
Carmarthenshire	Carmarthen	2
Wiltshire	Cheverell	2
Wiltshire	Chitterne	2
Wiltshire	Codford	2
Wiltshire	Collingbourne	2
Warwickshire	Coventry	2
Northamptonshire	Cranford	2
Wiltshire	Cricklade	2
Devon	Dartmouth	2
Kent	Deptford	2
Dorset	Dorchester	2
Worcestershire	Evesham	2
Yorkshire, West Riding	Ferry Fryston	2
Gloucestershire	Forest Of Dean	2
Norfolk	Forncett	2
Norfolk	Glandford and Bayfield	2
Lincolnshire	Great Limber and Brocklesby	2
Worcestershire	Great Witley and Martley	2
Suffolk	Hargrave and Southwell Park	2
Yorkshire, East Riding	Hull	2
Suffolk	Icklingham	2
Norfolk	Lamas and Little Hautbois	2
Cornwall	Landrake and St Erney	2
Cornwall	Launceston	2
Wiltshire	Lavington	2
Leicestershire	Leicester Forest	2
Norfolk	Long Stratton	2
Lincolnshire	Ludford	2
Dorset	Lulworth	2
Dorset	Lytchett	2
Wiltshire	Manningford	2
Wiltshire	Marlborough	2
Lincolnshire	Mumby	2
Suffolk	Newmarket	2
Wiltshire	Orcheston	2
Norfolk	Oxwick and Pattesley	2
Pembrokeshire	Pembroke	2
Cornwall	Perranuthnoe and St Hilary	2
Worcestershire	Pershore	2
Northamptonshire	Peterborough	2
Somerset	Pilton and North Wootton	2
Devon	Plymouth	2
Devon	Plympton	2
Norfolk	Poringland	2
Norfolk	Ranworth With Panxworth	2
Nottinghamshire	Retford	2
Kent	Romney	2
Norfolk	Rudham	2
Wiltshire	Savernake	2
Yorkshire, West Riding	Sawley and Tosside	2
Wiltshire	Sherston	2
Lincolnshire	Sleaford	2
Kent	Snodland and Paddlesworth	2
Lincolnshire	Somercotes	2
Norfolk	Somerton	2
Norfolk	South Walsham	2
Norfolk	Sporle and Palgrave	2
Middlesex	St Andrew Holborn and St George The Martyr	2
Cornwall	St Columb	2
Middlesex	St Giles in the Fields and St George Bloomsbury	2
Lincolnshire	Stoke	2
Buckinghamshire	Stony Stratford	2
Herefordshire	Sutton	2
Nottinghamshire	Sutton Bonington	2
Glamorganshire	Swansea	2
Somerset	Taunton	2
Herefordshire	Tedstone	2
Norfolk	Terrington	2
Norfolk	Thetford	2
Wiltshire	Tisbury	2
Norfolk	Upton and Fishley	2
Norfolk	Walpole	2
Norfolk	Walton	2
Norfolk	Warham	2
Warwickshire	Warwick	2
Norfolk	Weasenham	2
Suffolk	Whelnetham	2
Dorset	Whitchurch and Catherson	2
Cambridgeshire	Wisbech	2
Norfolk	Witchingham	2
Norfolk	Wretham	2

A.3 Variable construction

Riots before Swing (1758-1829). We collect new data on pre-1830 arsons and machine attacks from the British Library and Findmypast (2016).[30] We search for the words 'arson' and 'machine attack' within the universe of articles published in one of the 60 regional newspaper printed between 1750 and 1832. The search yielded a total of 6,392 articles for 'arson' and 15,986 articles for 'machine attack.' We read in full each of the 'arson' articles and a 35% random sample of the 'machine attack' articles. We first determine whether an article describes a recent episode of civil unrest. If it does, we manually geo-locate the event on the map of England (Southall and Burton, 2004). The final database contains 610 episodes of arson and 69 attacks on machines between 1758 and 1829. We validate this data by looking for similar articles during the Swing riots of 1830-32, and by comparing these episodes with Swing riots coded as 'arson' or 'attacks on machines' in the database compiled by Holland (2005). Both arsons and attacks on machines are very correlated between the two data sources: the t-stat of a regression of arsons is 4.53; the t-stat of a regression of machine attacks is 8.09.

Swing riots (1830-32). Data on Swing riot comes from a database compiled by the Family and Community Historical Research Society (Holland, 2005). The data contains a comprehensive list of Captain Swing incidents between January 1830 and December 1832. The information comes from judicial records and historical newspapers and contains date, parish, and type of crime perpetrated by rioters. We consider only episodes that happened between August 1830 and December 1832. For each of these episodes, we manually match the parish of the riot to the historical map of English and Welsh parishes (Southall and Burton, 2004). On this map, we identify the location of these riots with the county (variable GAZ_CNTY) and either the name of the parish (variable PAR) or the name of the place (variable PLA). In our baseline results, we use a variable that contains every episode listed in the database, irrespective of the nature of the protest.

Attacks on threshing machines during Swing (1830-32). This is a subset of the Swing riots from Holland (2005). We classify as attack on a threshing machine every event that was recorded as "MACHINE BREAKING (Threshing machines)".

Threshing machines before Swing (1800-29). We assemble a list of threshing machines in use before the riots from two data sources. The first is built from threshing machines advertisements found on English and Welsh newspapers. The second are the reports of threshing machines on the *General Views of Agriculture*. We collect newspaper advertisements from British Library and Findmypast (2016).[31] Within the universe of the 60 regional newspaper published between 1800 and 1830, we search for the exact string 'threshing machine.' We restrict our search to articles classified as either 'advertisement' or 'classifieds.' Next, we read in full each article retrieved, and determine whether it is relevant for our research. We consider relevant information any article that advertises the sale or the lease of a threshing machine or of a farm that lists a threshing machine among its assets. In one case, we also

[30] We collected these articles during the spring of 2019.

[31] See: http://www.britishnewspaperarchive.co.uk/. We collected these articles during the spring of 2016.

consider the information provided by a threshing machine manufacturer who lists name and location of their clients: these clients are farmers located in parishes all over the country (see Figure B.2). We drop all advertisements of threshing machines producers that only provide information about the location of the factory, usually an industrial town. We also only consider a single threshing machine whenever we find the same advertisement printed more than once. In the last step, we manually geo-locate each advertisement, and find the parish in which the threshing machine or the farm is located on the map prepared by Southall and Burton (2004).

We complement this source with a list of threshing machines we found on the *General Views of Agriculture* for all English counties. In the second editions of each of these publications, the surveyors devoted an entire chapter to threshing machines, relating information on every machine they found in the countryside, including the name of the owner and the place of operation. We locate each of these machines on the map of Southall and Burton (2004) and make sure that we do not double count any machine from the newspapers by comparing the names of the owners in the two sources. Whenever we link a parish to either an advertisement or a machine from the *General Views*, we add 1 to the number of threshing machines we find in that parish.

Threshing and mowing machines after Swing (1832-53). We collect information on agricultural machine in use in the 20 years following the riots from British Library and Findmypast (2016). We first select 8 years after the riots: 1832, 1835, 1838, 1841, 1844, 1847, 1850 and 1853. Next, we search in newspapers published in these years farm advertisements that mention either 'threshing machines,' or 'mowing machines.' We read each of these advertisements in full, and then locate them on the map of Southall and Burton (2004). The measure of agricultural machine diffusion is the sum of the threshing machine and mowing machine we found in each parish.

Patents before and after Swing (1813-1843). We digitize every patent registered in England between the 20th of November 1813 and the 15th of June 1843 from Woodcroft (1854). This publication reports, for every patent that was registered in England, the title, the date of registration, the name and occupation of the inventor(s) and the place where they lived. We digitize this information and locate the parish in which each of these inventors were living at the time of the registration. Whenever more than one inventor claims one patent, we assign to each of the parishes of these inventors a value equal to one divided by the numbers of inventors. We divide patents into two groups: those registered before the 31st of December 1829 and those registered between the 1st of January 1833 and the 15th of June 1843. We do not consider the patents registered during the years 1830-32 to avoid confounding the direct effect of riots on patenting activity.

Density (1801). Parish population comes from the 1801 Census of England (Southall et al., 2004): the original variable is POP_1801. We merge the census to the historical map of English and Welsh parishes using the Census variables county (ANC_CNTY) and parish (ANC_PAR). The total area of the parish (in square km) is calculated with ArcGIS based on the map of historical parishes of England and Wales described in Appendix A.2.

Density is 1801 population per square km. We use the natural logarithm of this variable in all regressions.

Share of workers (1801). We construct these variables with data from the 1801 Census of England (Southall et al., 2004). We calculate three shares: for agriculture, trade and other activities, using the variables OC_AGRIC, OC_TRADE and OC_OTHER. Census data come at the parish level and we merge it to the historical map of English and Welsh parishes as we did with the 1801 population.

Sex ratio (1801). We compute the sex ratio with data from the 1801 Census as the total number of men (variable MA_1801) divided by the total number of women (variable FE_1801). Census data come at the parish level and we merge it to the historical map of English and Welsh parishes as we did with the 1801 population. We use the natural logarithm of this variable in all regressions.

Share of land cultivated with cereals (1801). The 1801 Corn Returns record land use information for almost 4000 parishes (Turner, 2005). We merge the Crop Returns to the historical map of English and Welsh parishes using the Census variables county (ANC_CNTY) and parish (ANC_PAR). We construct the share of land cultivated with cereals as the sum of the area devoted to wheat, oat, barley and rye (variables $WHEAT$, $OATS$, $BARLEY$ and RYE) divided by the total area cultivated.

Ratio of sales of wheat to oat. Brunt and Cannon (2013) digitized information from the crop returns. Their database records weekly information on quantity and value sold for different crops across 174 English market towns in 1820-30. We assign each English parish to the closest market town based on the distance to the centroid of the parish. We construct two ratios: the first, is the ratio of the average value of wheat sold to the average value of oat sold. The second is the ratio of the average quantity of wheat sold to the average quantity of oat sold.

Distance to Elham (first riot). We construct this variable as the distance of the centroid of every parish in our map to Elham, the parish that saw the first episode of the Swing riots according to Griffin (2012). We use the natural logarithm of this variable in all regressions.

Distance to closest town with a newspaper. To construct this variable, we first determine which of the newspapers stored on the *British Newspaper Archive* was in print before 1830. Next, we manually geo-code the cities in which these newspapers were printed. We then calculate the distance of the centroid of every parish in our map to each of these cities. Finally, we keep only the distance to the closest city. We use the natural logarithm of this variable in all regressions.

Distance to closest manufacturing city. We consider 15 manufacturing centers in 1801: Stockport in Cheshire, Blackburn, Bolton-le-Moors, Liverpool, Manchester, Oldham, Preston and Whalley in Lancashire, London, Norwich in Norfolk, Wolverhampton and Birmingham in Warwickshire and three cities in Yorkshire, West Riding: Halifax, Leeds and Sheffield. We identify these cities by selecting the top 15 parishes in terms of 1801 share of employment in "trade" among those that had at least 18000 inhabitants in 1801. In the 1801 census, these centers had on average 46 percent of the workers employed in trade and less than 2.7 percent employed in agriculture. In the rest of English parishes, 11.6 percent of workers were chiefly employed in trade and 38.6 percent in agriculture. We use the coordinates of the centroid of these cities and of every parish in England to construct the distance of every parish to the closest of manufacturing center. We then divide the sample into two groups: above and below the median distance to these cities. The median parish in terms of distance to manufacturing cities is Waterstock in Oxfordshire which lies 74 km from Blackburn.

Share of soil that is heavy. We collect information on soil composition from the *British Geological Survey Soil Parent Material Model.* The dataset focuses upon the material from which top soils and subsoils develop (A and B horizons). The original data is a raster that covers the land mass of Britain on a grid of 1×1 km. We superimpose the raster on our historical map of English and Welsh parishes by intersecting every cell of the raster with the parish it falls in. We use the soil group variable to classify cells into light and heavy soils. Light soils are soils rich in sand and silt. Heavy soils are soils rich in clay and to a lesser extent loam. For every parish we take the share under heavy soil of all the cells that fall inside the parish.

Cereal suitability index. We construct our own cereal suitability index based on detailed weather data and an agronomic model from FAO's ECOCROP.[32] Weather data is from Hijmans et al. (2005): they provide average monthly precipitation and three average monthly temperatures (minimum, maximum and mean) over a grid of 30×30 arc-seconds. Averages are computed over the years 1960-90. We use these data to estimate cereal suitability following Wigton-Jones (2019): Appendix A.4 describes the procedure in detail. It yields an index for every grid cell covering England and Wales: we resample this raster on a grid of 2.88 arc-seconds with the "nearest" method. Next, we superimpose this raster on our historical map of English and Welsh parishes. For every cell of the raster we take the centroid and assign it to the parish where the centroid falls. Finally, for each parish we take the average index of all the cells that fall inside the parish.

Abnormal precipitation (spring and summer 1830). We take historical precipitation from Pauling et al. (2006). They used documentary evidence and natural proxies to prepare a database with seasonal precipitation for the period 1500-1900 over a 0.5×0.5 degrees grid covering Europe (approximately 55.5×55.5 km). To construct abnormal precipitation in the spring (summer) of 1830 across England and Wales, we take average spring (summer) precipitation in 1830 and subtract the average spring (summer) precipitation in the years 1800-1828. We do this for every cell that covers the British Isle, obtaining a new raster with the abnormal precipitation in the spring (summer) of 1830. Next, we resample this raster on a finer grid of 88.8×88.8 m with the "nearest" method, and we superimpose it to our historical map of English and Welsh parishes described above. For every cell of the raster we take its centroid and assign it to the parish where the centroid falls. Finally, for every parish we calculate the average abnormal precipitation in the spring (summer) of 1830 of every cell that falls inside the parish.

[32]See http://ecocrop.fao.org/ecocrop/srv/en/home.

Abnormal temperature (fall 1830). Historical temperature is from Luterbacher et al. (2004). They used documentary evidence and natural proxies to prepare a database with seasonal temperature for the period 1500-1900 over a 0.5×0.5 degrees grid covering Europe (approximately 55.5×55.5 km). To construct abnormal temperature in the fall of 1830 across England and Wales, we follow the same procedure described for abnormal precipitation. We take average fall temperature in 1830 and subtract the average fall temperature in the years 1800-1828. We do this for every cell that covers the British Isle, obtaining a new raster with the abnormal fall temperature of 1830. Next, we resample this raster on a finer grid of 88.8×88.8 m with the "nearest" method, and we superimpose it to our historical map of English and Welsh parishes described above. For every cell of the raster we take its centroid and assign it to the parish where the centroid falls. Finally, for every parish we calculate the average abnormal temperature in the fall of 1830 of every cell that falls inside the parish.

Share of land enclosed (1800). Data on enclosures are from Gonner (1912). In the tables on pages 270-278, Gonner reports information on the percentage of land in commons that was enclosed before 1870. He collected information across 340 'registration districts' covering 6,705 parishes. In order to estimate the percentage of land enclosed *before* the spread of threshing machines in 1800, we combine the information on this table with information from the table on page 279-281 of the same book. In this second table, Gonner reports the share of land in commons enclosed in each decade between 1760 and 1870 for every county in England and Wales. We estimate the share of land enclosed in 1800 by multiplying district-level enclosures in 1870 with the proportion of enclosures that happened before 1800 in the county of every district. We use the registration district reported in the 1801 Census to match each parish to its registration district. The parishes in the registration districts of Biggleswade (Bedford), Billericay, Colchester, Ongar, Romford (Essex) and Market Harborough (Leicester) have the median level of enclosure: we define parishes with 'high' enclosures those parishes with more than this level of enclosures.

Poor Rates per capita (1801). We calculate poor relief based on data from the "Poor Law Report" of 1834.[33] From the report, we digitized the population in 1801 (first entry of question A on the questionnaire) and *Poor Rates* collected in 1803 (first entry of question B on the questionnaire). The variable is calculated as the total value of poor rates in 1803 divided by the 1801 population in the parish.

Unemployment (winter and summer 1834). We collect data on winter and summer unemployment from the "Poor Law Report" of 1834. The report is a Parliamentary inquiry that collects information on a selected sample of parishes across England and Wales. Officials surveyed a total of 1,391 parishes, and recorded the answers provided by local informants. Not all of these places provided valid answers to every question and we have valid unemployment data for 574 parishes. To reconstruct parish-level unemployment, we digitize the answers of question 5 and 6.[34] Question 5 reads: 'number of agricultural labourers in your parish?'; question 6 reads: 'number of labourers generally out of employment, and how

[33]Full title: *Report from his Majesty's commissioners for inquiring into the administration and practical operation of the Poor Laws.*

[34]Officials were sent to survey parishes in 3 different waves between 1833 and 1834, and the questionnaire

maintained in summer and in winter?' We construct unemployment as number of labourers out of employment divided by the total number of labourers: we do this separately for winter and for summer and we set to missing 6 parishes where unemployment is above 100 percent. We construct relative unemployment as the difference between winter and summer unemployment.

they asked varied slightly between these waves. Question 5 and 6 in the first two issues became question 6 and 7 in the 3rd issue. The content of the answers did not change.

A.4 Cereal suitability index

This section describes the construction of our cereal suitability index from FAO's agronomic model ECOCROP.[35] It follows closely the excellent work of Wigton-Jones (2019).

1. The index requires the following 8 parameters:

   - minimum temperature ($\underline{\theta}$): temperature below which cereals die;
   - optimal temperature range ($\underline{\theta}^*$—$\overline{\theta}^*$): optimal temperature range for growing cereals;
   - maximum temperature ($\overline{\theta}$): temperature above which cereals die;
   - minimum rainfall ($\underline{\rho}$): cumulative rainfall during growing season below which cereals die;
   - optimal rainfall range ($\underline{\rho}^*$—$\overline{\rho}^*$): optimal cumulative rainfall range during growing season;
   - maximum rainfall ($\overline{\rho}$): cumulative rainfall during growing season above which cereals die.

2. We use these parameters together with average monthly temperature (T_m^{avg}) and rainfall (R_m^{avg}) to construct two sets of monthly indexes: temperature suitability (I_m^T) and rainfall suitability (I_m^R). The indexes take the following values:

$$I_m^T = \begin{cases} 0 & \text{if} & & T_m^{\text{avg}} & < \underline{\theta} \\ f_1(T_m^{\text{avg}}) & \text{if} & \underline{\theta} \leq & T_m^{\text{avg}} & < \underline{\theta}^* \\ 1 & \text{if} & \underline{\theta}^* \leq & T_m^{\text{avg}} & < \overline{\theta}^* \\ f_2(T_m^{\text{avg}}) & \text{if} & \overline{\theta}^* \leq & T_m^{\text{avg}} & < \overline{\theta} \\ 0 & \text{if} & \overline{\theta} \leq & T_m^{\text{avg}} & \end{cases}$$

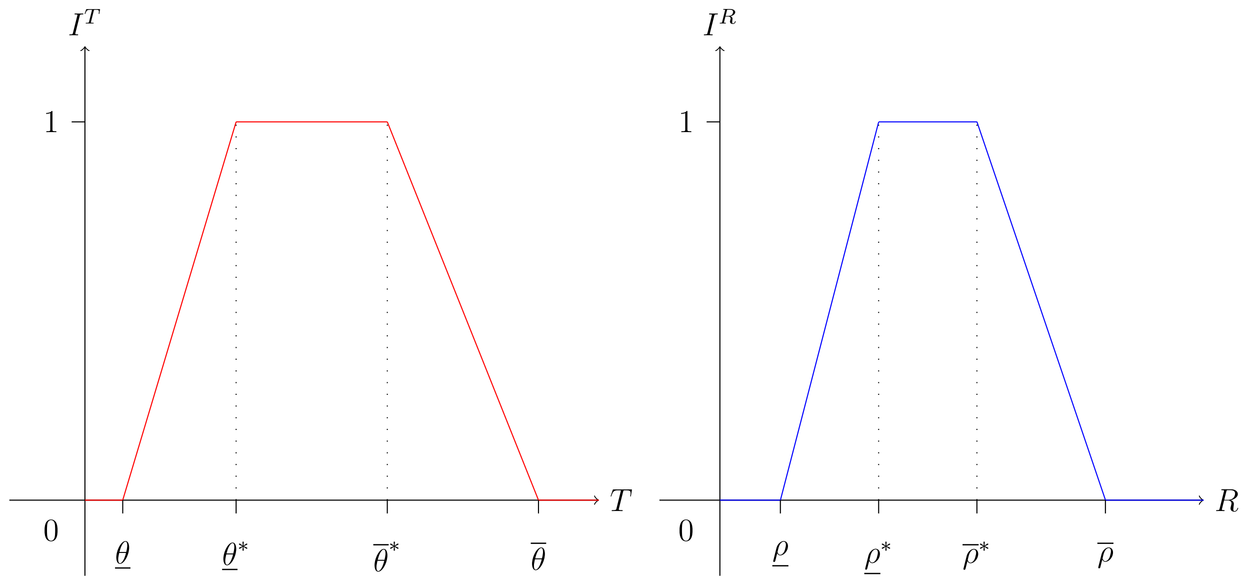
$$I_m^R = \begin{cases} 0 & \text{if} & & R_m^{\text{avg}} & < \underline{\rho} \\ g_1(R_m^{\text{avg}}) & \text{if} & \underline{\rho} \leq & R_m^{\text{avg}} & < \underline{\rho}^* \\ 1 & \text{if} & \underline{\rho}^* \leq & R_m^{\text{avg}} & < \overline{\rho}^* \\ g_2(R_m^{\text{avg}}) & \text{if} & \overline{\rho}^* \leq & R_m^{\text{avg}} & < \overline{\rho} \\ 0 & \text{if} & \overline{\rho} \leq & R_m^{\text{avg}} & \end{cases}$$

3. We choose the functions $f_1(T^{\text{avg}})$, $f_2(T^{\text{avg}})$, $g_1(R^{\text{avg}})$ and $g_2(R^{\text{avg}})$ so that the index function is linear and continuous (see Figure A.1).

4. We also set $I_m^T = 0$ whenever the mean maximum (minimum) temperature rises above the maximum (falls below the minimum) temperature that kills cereals.

[35] See http://ecocrop.fao.org/ecocrop/srv/en/home.

Figure A.1: Examples of temperature and rainfall suitability indexes



5. We obtain monthly indexes by multiplying temperature and rainfall indexes: $I_m = I_m^T \times I_m^R$.

6. Cereals need 100-120 days to grow. As Wigton-Jones (2019), we do not take a stance on which month the growing season should start. Instead, we calculate separate indexes for each of the 12 months. We consider that during any spell of 4 consecutive months, the worse conditions will determine productivity (Liebig's law). Thus, for every month we take the minimum suitability index among the 4 months starting then: this is the index of that growing season. We assume that farmers will select the best growing season among the 12 possible, and take the highest of the 12 indexes to be the suitability index.

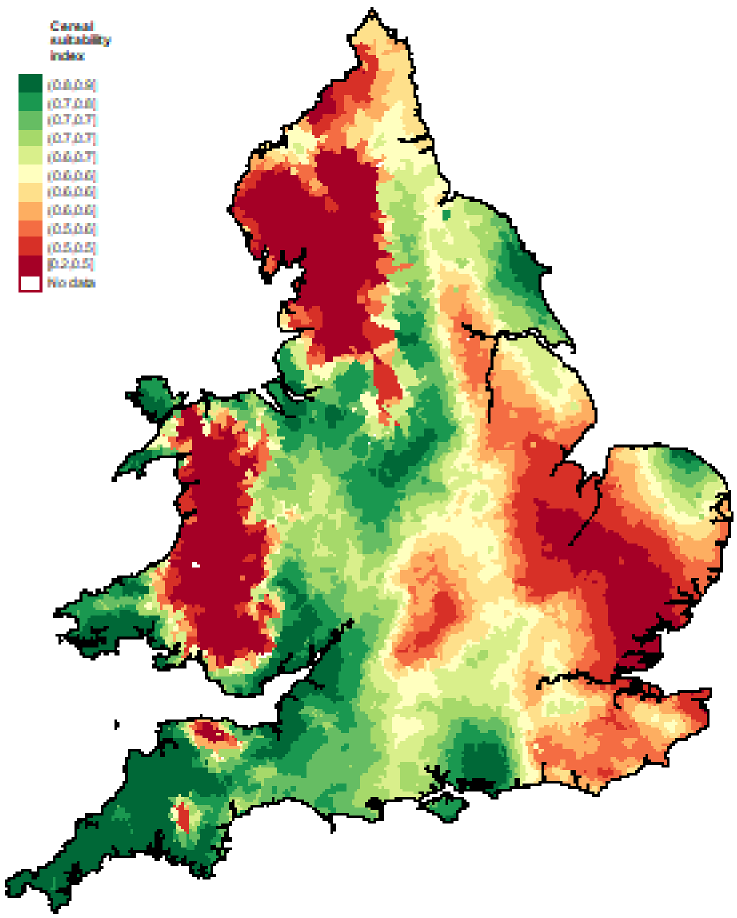
FAO provides parameters for 4 cereals: wheat (*triticum aestivum*), oat (*avena sativa*), barley (*hordeum vulgare*) and rye (*secale cereale*). However, it provides no parameter for cereals as a whole. Because we want to capture weather conditions that make cultivation of *any* cereal possible, for every parameter we select the most constraining among the values provided for the 4 cereals. Table A.3 provides the parameters of the four crops and the combined parameter for the cereal family.

Figure A.2 plots the cereal suitability index on the map of England.

Table A.3: FAO's ECOCROP parameters.

		Wheat	Oat	Barley	Rye	Cereals
Minimum temperature (°C)	$\underline{\theta}$	5	5	2	3	5
Minimum optimal temperature (°C)	$\underline{\theta}^*$	15	16	15	15	16
Maximum optimal temperature (°C)	$\overline{\theta}^*$	23	20	20	20	20
Maximum temperature (°C)	$\overline{\theta}$	27	30	40	31	27
Minimum rainfall (mm)	$\underline{\rho}$	99	82	66	132	132
Minimum optimal rainfall (mm)	$\underline{\rho}^*$	247	197	164	197	247
Maximum optimal rainfall (mm)	$\overline{\rho}^*$	296	329	329	329	296
Maximum rainfall (mm)	$\overline{\rho}$	526	493	658	658	493

Figure A.2: Cereal suitability index

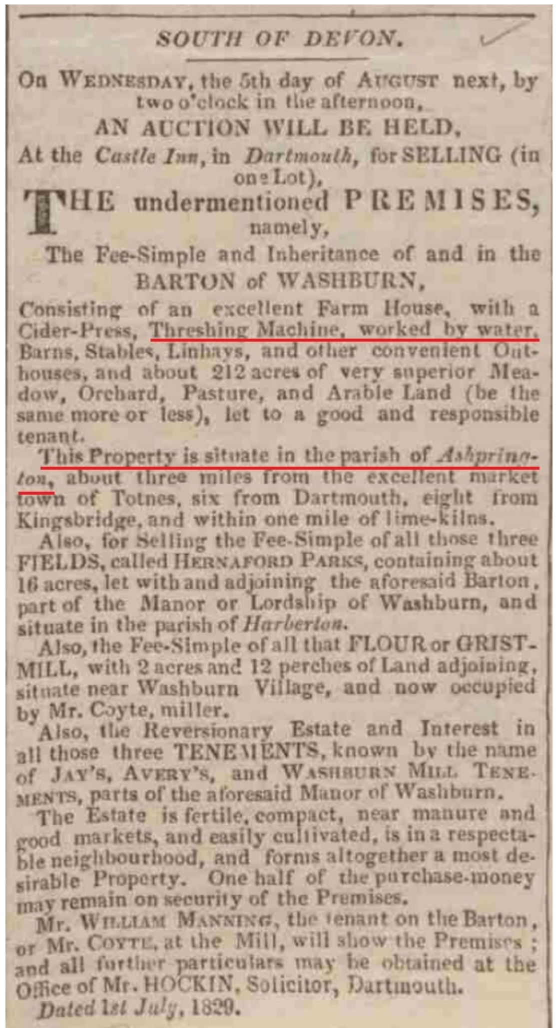


Notes. Cereal suitability index. Source: own calculation based on weather data from Hijmans et al. (2005) and parameters from the FAO-ECOCROP model.

B Additional results

B.1 Additional figures

Figure B.1: Example of an advertisement for a 'threshing machine'



SOUTH OF DEVON.

On WEDNESDAY, the 5th day of AUGUST next, by two o'clock in the afternoon,

AN AUCTION WILL BE HELD,

At the *Castle Inn*, in *Dartmouth*, for SELLING (in one Lot),

THE undermentioned PREMISES, namely,

The Fee-Simple and Inheritance of and in the BARTON of WASHBURN,

Consisting of an excellent Farm House, with a Cider-Press, Threshing Machine, worked by water, Barns, Stables, Linhays, and other convenient Out-houses, and about 212 acres of very superior Meadow, Orchard, Pasture, and Arable Land (be the same more or less), let to a good and responsible tenant.

This Property is situate in the parish of *Ashprington*, about three miles from the excellent market town of Totnes, six from Dartmouth, eight from Kingsbridge, and within one mile of lime-kilns.

Also, for Selling the Fee-Simple of all those three FIELDS, called HERNAFORD PARKS, containing about 16 acres, let with and adjoining the aforesaid Barton, part of the Manor or Lordship of Washburn, and situate in the parish of *Harberton*.

Also, the Fee-Simple of all that FLOUR or GRIST-MILL, with 2 acres and 12 perches of Land adjoining, situate near Washburn Village, and now occupied by Mr. Coyte, miller.

Also, the Reversionary Estate and Interest in all those three TENEMENTS, known by the name of JAY'S, AVERY'S, and WASHBURN MILL TENEMENTS, parts of the aforesaid Manor of Washburn.

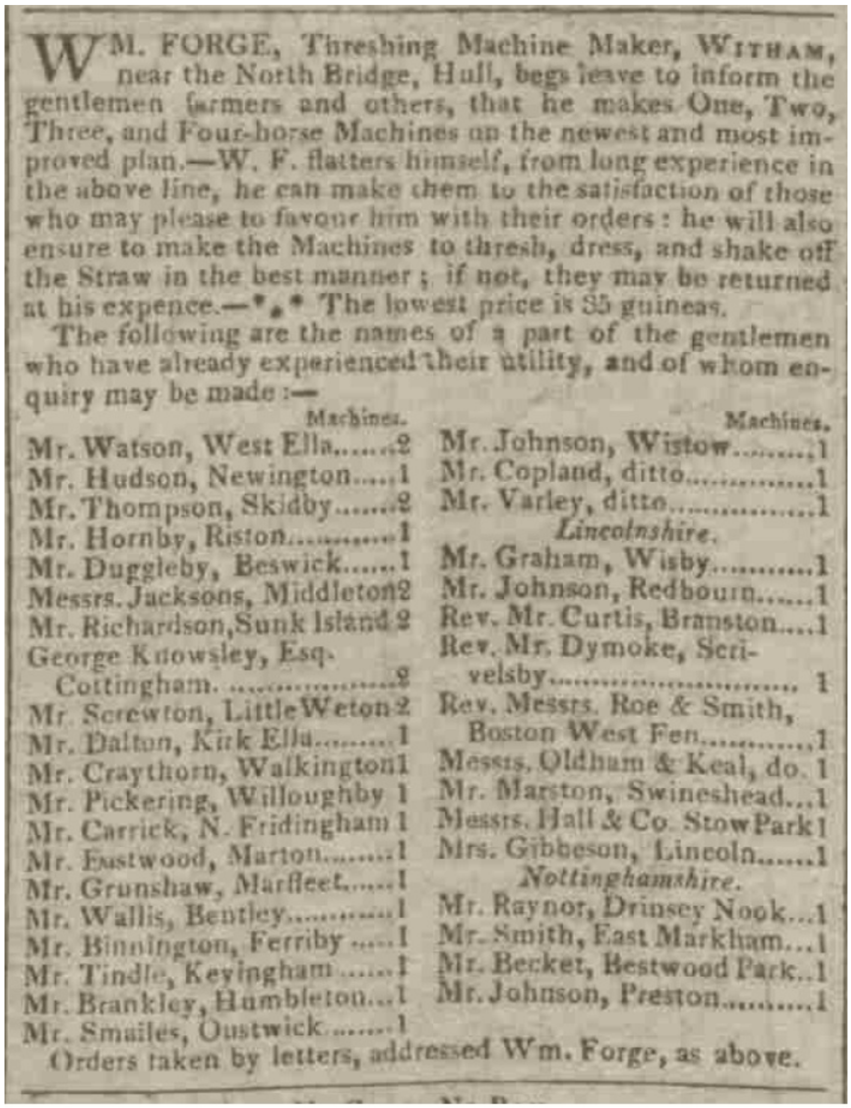
The Estate is fertile, compact, near manure and good markets, and easily cultivated, is in a respectable neighbourhood, and forms altogether a most desirable Property. One half of the purchase-money may remain on security of the Premises.

Mr. WILLIAM MANNING, the tenant on the Barton, or Mr. COYTE, at the Mill, will show the Premises; and all further particulars may be obtained at the Office of Mr. HOCKIN, Solicitor, Dartmouth.

Dated 1st July, 1829.

Notes. On July the 1st, 1829, the Sherborne Mercury advertised the sale of a farm in the parish of Ashprington (Devon). We count this advertisement as an indication that threshing machines are used in this parish because the farm includes a 'threshing machine' among the assets that went on sale. Source: British Library and Findmypast (2016).

Figure B.2: Example of an advertisement.



WM. FORGE, Threshing Machine Maker, WITHAM, near the North Bridge, Hull, begs leave to inform the gentlemen farmers and others, that he makes One, Two, Three, and Four-horse Machines on the newest and most improved plan.—W. F. flatters himself, from long experience in the above line, he can make them to the satisfaction of those who may please to favour him with their orders: he will also ensure to make the Machines to thresh, dress, and shake off the Straw in the best manner; if not, they may be returned at his expence.—*,* The lowest price is 35 guineas.

The following are the names of a part of the gentlemen who have already experienced their utility, and of whom enquiry may be made:—

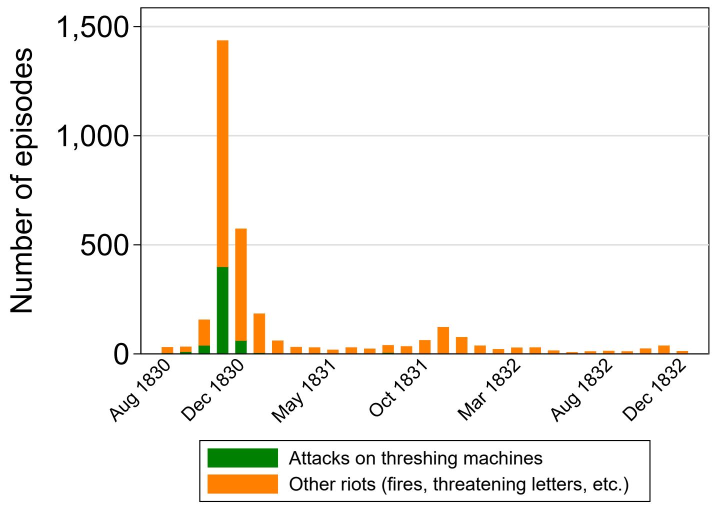
	Machines.
Mr. Watson, West Ella	2
Mr. Hudson, Newington	1
Mr. Thompson, Skidby	2
Mr. Hornby, Riston	1
Mr. Duggleby, Beswick	1
Messrs. Jacksons, Middleton	2
Mr. Richardson, Sunk Island	2
George Knowsley, Esq. Cottingham	2
Mr. Screwton, Little Weton	2
Mr. Dalton, Kirk Ella	1
Mr. Craythorn, Walkington	1
Mr. Pickering, Willoughby	1
Mr. Carrick, N. Fridingham	1
Mr. Eastwood, Marton	1
Mr. Grunshaw, Marfleet	1
Mr. Wallis, Bentley	1
Mr. Binnington, Ferriby	1
Mr. Tindle, Keyingham	1
Mr. Brankley, Humbleton	1
Mr. Smailes, Oustwick	1

	Machines.
Mr. Johnson, Wistow	1
Mr. Copland, ditto	1
Mr. Varley, ditto	1
Lincolnshire.	
Mr. Graham, Wisby	1
Mr. Johnson, Redbourn	1
Rev. Mr. Curtis, Branston	1
Rev. Mr. Dymoke, Scrivelsby	1
Rev. Messrs. Roe & Smith, Boston West Fen	1
Messrs. Oldham & Keal, do.	1
Mr. Marston, Swineshead	1
Messrs. Hall & Co. Stow Park	1
Mrs. Gibbeson, Lincoln	1
Nottinghamshire.	
Mr. Raynor, Drinsey Nook	1
Mr. Smith, East Markham	1
Mr. Becket, Bestwood Park	1
Mr. Johnson, Preston	1

Orders taken by letters, addressed Wm. Forge, as above.

Notes. On February the 2nd, 1808, the *Stamford Mercury* published the notice of William Forge, a threshing machine maker, who advertised his product by suggesting to contact one of his past customers. We code each of the parishes listed above as parishes in which at least one threshing machine is in operation. Source: British Library and Findmypast (2016).

Figure B.3: Swing riots over time.

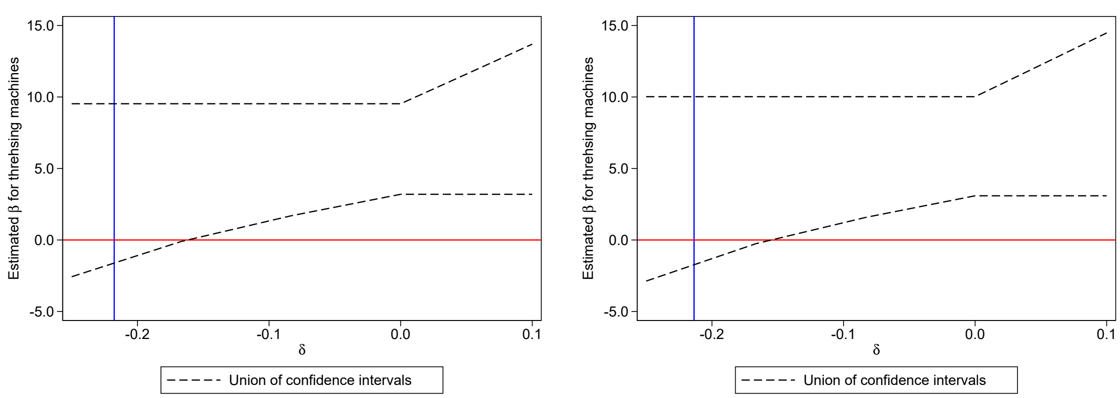


Notes. In green: attacks on threshing machines. In orange: all other riots associated to Swing: including threatening letters and arson attacks. Source: Holland (2005).

Figure B.4: Plausible exogeneity test

(a) Controls

(b) Controls and region fixed effects



Notes. Robustness: effect of violation of exclusion restriction (Conley et al., 2012). Union of confidence intervals of the IV estimates (y-axis) when the exclusion restriction is violated (x-axis). Panel (a): regression includes all controls as in col. 7 of Table 1. Panel (b): regression includes all controls and 5 region fixed effects as in col. 8 of Table 1. Blue vertical lines: point estimate of the reduced form coefficient (cols. 5-6 of Table 1).

B.2 Additional tables

Table B.1: Threshing machines and the labor market.

	Unemployment: winter - summer			
	(1)	(2)	(3)	(4)
No. of threshers	0.025	0.021	0.022	0.019
	[0.007]	[0.007]	[0.007]	[0.008]
log 1801 density		0.021	0.014	0.012
		[0.006]	[0.006]	[0.006]
Share of agricultural workers in 1801			-0.017	-0.023
			[0.016]	[0.016]
log 1801 sex ratio			-0.032	-0.031
			[0.032]	[0.031]
log distance to Elham			-0.033	-0.022
			[0.009]	[0.014]
log distance to newspaper			0.011	0.013
			[0.006]	[0.006]
Constant	0.053	-0.027	0.144	0.068
	[0.004]	[0.020]	[0.060]	[0.087]
Region fixed effects (5)	No	No	No	Yes
R^2	0.010	0.032	0.081	0.091
Mean dependent variable	0.055	0.055	0.055	0.055
Observations	574	574	574	574

Notes: Threshing machines and the labor market. The dependent variable in is winter unemployment rate minus summer unemployment rate. Robust standard errors in parentheses.

Table B.2: Basic correlations: type of unrest.

No. of	Threshers attacked		Other riots	
	(1)	(2)	(3)	(4)
No. of threshers	0.097	0.087	0.292	0.266
	[0.029]	[0.029]	[0.054]	[0.054]
log 1801 density	0.007	0.006	0.094	0.093
	[0.004]	[0.004]	[0.015]	[0.016]
Share of agricultural workers in 1801	0.031	0.027	-0.095	-0.083
	[0.016]	[0.016]	[0.036]	[0.036]
log 1801 sex ratio	-0.038	-0.032	-0.144	-0.161
	[0.012]	[0.013]	[0.036]	[0.037]
log distance to Elham	-0.077	-0.048	-0.248	-0.169
	[0.012]	[0.021]	[0.023]	[0.035]
log distance to newspaper	-0.001	-0.001	0.023	0.020
	[0.005]	[0.005]	[0.016]	[0.017]
Constant	0.421	0.246	1.179	0.768
	[0.071]	[0.125]	[0.123]	[0.191]
Region fixed effects (5)	No	Yes	No	Yes
R^2	0.023	0.026	0.051	0.058
Mean share	0.053	0.053	0.255	0.255
Observations	9674	9674	9674	9674

Notes: Threshers and type of unrest. All columns report OLS estimates of Equation (1). Col. 1-2: dependent variable is number of attacks on threshing machines during 1830-32. Col. 3-4: dependent variable is number of 1830-32 riots that did not involve the attack to a threshing machine. Robust standard errors in brackets.

Table B.3: Pre-trends in arsons and machine attacks.

No. of	Riots (1758-1832)			
	(1)	(2)	(3)	(4)
No. of threshers in the 1800	-0.074	-0.070		
	[0.087]	[0.087]		
No. of threshers in the 1810	-0.015	-0.012		
	[0.036]	[0.036]		
No. of threshers in the 1820	0.147	0.148		
	[0.067]	[0.068]		
No. of threshers in the 1830	0.207	0.192		
	[0.054]	[0.054]		
Heavy soil × 1800s			-0.000	0.000
			[0.001]	[0.001]
Heavy soil × 1810s			0.001	-0.000
			[0.005]	[0.005]
Heavy soil × 1820s			-0.016	-0.009
			[0.014]	[0.015]
Heavy soil × 1830-32			-0.118	-0.117
			[0.018]	[0.018]
Cereal suitability index × 1800s			-0.005	-0.005
			[0.005]	[0.005]
Cereal suitability index × 1810s			-0.128	-0.125
			[0.036]	[0.036]
Cereal suitability index × 1820s			-0.266	-0.212
			[0.091]	[0.089]
Cereal suitability index × 1830-32			0.062	0.176
			[0.070]	[0.074]
log density, agricultural share & log sex ratio	Yes	Yes	Yes	Yes
log distance to newspaper × year fixed effects	Yes	Yes	Yes	Yes
log distance to Elham × year fixed effects	Yes	Yes	Yes	Yes
Parish & year fixed effects	Yes	Yes	Yes	Yes
Region (5) × year fixed effects	No	Yes	No	Yes
R^2	0.275	0.277	0.273	0.276
Observations	48649	48649	48637	48637

Notes: Pre-1830 riots. Dependent variable is number of arsons or attacks on production machines between 1758 and 1832. Data source is British Library and Findmypast (2016) for pre-1830 events and Holland (2005) for 1830-32: see Appendix A for details. Col. 1-2: correlation with threshers. Col. 3-4: correlation with heavy soil. Standard errors clustered at parish level in brackets.

Table B.4: Sanity check: do light soils predict wheat prevalence?

	log wheat / oat value sold 1820-30				log wheat / oat quantity sold 1820-30			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of area in parish whose soil is heavy	-0.072	-0.069	-0.067	-0.050	-0.073	-0.071	-0.068	-0.053
	[0.032]	[0.029]	[0.030]	[0.020]	[0.034]	[0.030]	[0.031]	[0.022]
Wheat / oat suitability index		0.074	0.140	0.053		0.053	0.138	0.064
		[0.123]	[0.132]	[0.102]		[0.130]	[0.139]	[0.108]
log 1801 density			-0.007	-0.011			-0.007	-0.011
			[0.009]	[0.009]			[0.009]	[0.009]
Share of agricultural workers in 1801			0.010	-0.009			0.006	-0.011
			[0.012]	[0.010]			[0.013]	[0.011]
log 1801 sex ratio			-0.020	0.009			-0.015	0.013
			[0.014]	[0.012]			[0.015]	[0.012]
log distance to Elham			-0.022	0.025			-0.027	0.023
			[0.024]	[0.017]			[0.026]	[0.019]
log distance to newspaper			0.017	0.016			0.015	0.016
			[0.016]	[0.016]			[0.017]	[0.017]
Constant	1.254	1.182	1.209	0.939	1.191	1.140	1.180	0.886
	[0.031]	[0.100]	[0.127]	[0.164]	[0.033]	[0.106]	[0.137]	[0.179]
Region fixed effects (5)	No	No	No	Yes	No	No	No	Yes
R^2	0.022	0.024	0.034	0.101	0.019	0.020	0.028	0.082
Mean dependent variable	1.217	1.217	1.217	1.217	1.153	1.153	1.153	1.153
Observations	9562	9562	9562	9562	9562	9562	9562	9562

Notes: wheat and oat sales and soil characteristics. Col. 1-4: dependent variable is the ratio of the values sold of wheat to oat. Col. 5-8: dependent variable is the ratio of the quantities sold of wheat to oat. Market data is from Brunt and Cannon (2013). Standard errors clustered at the level of the closest market town ($G = 174$) in brackets.

Table B.5: Balance table.

	Coefficient of heavy soil: Unconditional	Coefficient of heavy soil: Conditional on cereal suitability	Mean dep. variable	Observations
Share of land cultivated with cereals 1801	0.003	0.001	0.837	3859
	[0.006]	[0.006]		
log 1801 density	0.044	0.004	3.646	9674
	[0.028]	[0.029]		
Share agricultural workers 1801	0.005	0.006	0.386	9674
	[0.007]	[0.008]		
Share trade workers 1801	0.005	0.006	0.117	9674
	[0.004]	[0.004]		
Share other workers 1801	0.009	0.012	0.497	9674
	[0.008]	[0.008]		
log 1801 sex ratio	0.008	0.004	-0.025	9674
	[0.006]	[0.006]		
log distance to Elham	0.001	0.108	5.325	9674
	[0.017]	[0.016]		
log distance to newspaper	0.016	0.035	2.950	9674
	[0.020]	[0.021]		
Poor rates per capita 1800	0.029	0.032	0.695	1251
	[0.033]	[0.033]		

Notes: Balance of heavy soils relative to pre-existing characteristics. Col. 1: coefficients of separate bi-variate regressions. Dependent variable is listed on the left; explanatory variable is share of heavy soil. Col. 2: coefficients separate regressions. Dependent variable is listed on the left; explanatory variables are share of heavy soil and cereal suitability index. Only the coefficient of share of heavy soil is reported. Robust standard errors in brackets.

Table B.6: Aggravating circumstances: distance to closest industrial town.

	Distance to industrial town					
	All	Distant	Close	All	Distant	Close
No. of threshers	0.389	0.543	0.171	0.353	0.455	0.183
	[0.071]	[0.107]	[0.066]	[0.071]	[0.107]	[0.066]
log 1801 density	0.101	0.143	0.081	0.099	0.162	0.078
	[0.018]	[0.035]	[0.017]	[0.018]	[0.037]	[0.017]
Share of agricultural workers in 1801	-0.065	0.007	-0.144	-0.056	-0.009	-0.127
	[0.044]	[0.067]	[0.055]	[0.043]	[0.066]	[0.054]
log 1801 sex ratio	-0.181	-0.112	-0.187	-0.193	-0.098	-0.208
	[0.042]	[0.068]	[0.055]	[0.043]	[0.071]	[0.056]
log distance to Elham	-0.325	-0.374	-0.297	-0.217	-0.200	-0.356
	[0.029]	[0.046]	[0.038]	[0.045]	[0.057]	[0.082]
log distance to newspaper	0.022	0.025	0.024	0.019	0.056	0.024
	[0.018]	[0.024]	[0.027]	[0.019]	[0.027]	[0.031]
Constant	1.600	1.725	1.516	1.014	0.589	1.858
	[0.153]	[0.225]	[0.233]	[0.251]	[0.309]	[0.469]
Region fixed effects (5)	No	No	No	Yes	Yes	Yes
R^2	0.057	0.082	0.040	0.064	0.105	0.043
Mean dependent variable	0.308	0.308		0.308	0.308	
p-value Close = Distant			0.003			0.031
Observations	9674	4785	4889	9674	4785	4889

Notes: Aggravating circumstances: distance to closest industrial town. Dependent variable: number of Swing riots. The table reports results after splitting the sample according to the distance to the closest industrial town. Col. 1 and 4: baseline results (full sample); Col. 2 and 5: results for 4785 parishes above the median parish in terms of distance to industrial town; Col. 3 and 6: results for 4889 parishes below median parish. See Appendix A.3 for details. Robust standard errors in brackets.

Table B.7: Aggravating circumstances: enclosures.

	Share land enclosed					
	All	High	Low	All	High	Low
No. of threshers	0.462	0.615	0.215	0.398	0.555	0.162
	[0.085]	[0.115]	[0.099]	[0.085]	[0.116]	[0.099]
log 1801 density	0.169	0.129	0.208	0.176	0.152	0.204
	[0.022]	[0.033]	[0.028]	[0.022]	[0.034]	[0.028]
Share of agricultural workers in 1801	0.017	-0.154	0.189	0.009	-0.145	0.170
	[0.057]	[0.081]	[0.081]	[0.056]	[0.081]	[0.078]
log 1801 sex ratio	-0.193	-0.145	-0.245	-0.161	-0.117	-0.208
	[0.051]	[0.073]	[0.072]	[0.053]	[0.073]	[0.073]
log distance to Elham	-0.228	-0.325	-0.217	0.037	-0.073	0.064
	[0.037]	[0.061]	[0.047]	[0.064]	[0.078]	[0.109]
log distance to newspaper	0.049	-0.013	0.101	0.019	-0.059	0.096
	[0.022]	[0.033]	[0.029]	[0.025]	[0.038]	[0.034]
Constant	0.737	1.682	0.286	-0.624	0.468	-1.293
	[0.226]	[0.393]	[0.274]	[0.381]	[0.501]	[0.638]
Region fixed effects (5)	No	No	No	Yes	Yes	Yes
R^2	0.040	0.055	0.037	0.052	0.069	0.046
Mean dependent variable	0.345	0.384		0.345	0.384	
p-value Low = High			0.009			0.010
Observations	6715	3307	3408	6715	3307	3408

Notes: Aggravating circumstances:enclosures and unrest. Dependent variable is number of Swing riots in all columns. The table reports results after splitting the sample according to the 1800 level of enclosures. Columns 1, and 4: baseline results (full sample); columns 2 and 5: results for 3307 parishes above the median parish in terms of enclosures; columns 3 and 6: results for 3408 parishes below median parish. See Appendix A.3 for details. Robust standard errors in brackets.

B.3 Productivity of threshing machines

In this section, we attempt to quantify the productivity gains of threshing machines relative to manual labor. Contemporary observers recognized quickly the productivity gains offered by threshing machines (Donaldson, 1794; Batchelor, 1813, p.210).[36] However, there exists no systematic analysis of productivity for the machines in use in 1800, nor are we aware of any attempt to determine the productivity of machines operated with different power sources.

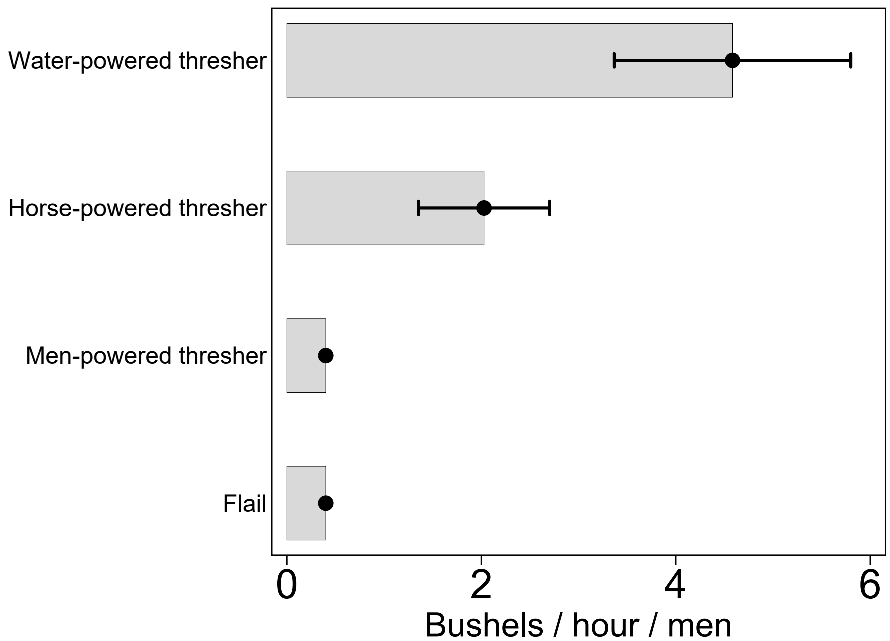
We source information on machine productivity from the county surveys of the *General View of Agriculture*. Sir John Sinclair commissioned the *General Views* as president of the Board of Agriculture in the 1790s, and professional agronomists prepared these documents under the supervision of Arthur Young. Separate volumes cover each county, and the commission surveyed most counties twice: once in 1790s and a second time in the 1810s. We collect all editions covering English counties: a total of 38 separate volumes. All of the *General Views* published in the 1810s, and several of those that appeared in the 1790s contain a chapter on threshing machines. We read these chapters in full, and collect all information that is useful to determine the productivity of these machines. The officials who prepared these chapters toured the English countryside and took detailed notes of every threshing machine they found. A typical entry in this chapter lists owner and location of the machine, as well as material and shape of each different component. It also reports the mode of operation, the number of men, women and children required to move it and the average quantity of wheat that the machine could thresh in a given amount of time.

We find 121 separate machines in the *General Views*. To calculate productivity we require information on wheat threshed per unit of time, number of people needed to operate the machine and the main source of power for the machine. Under these constraints, we are able to calculate productivity for 24 horse-powered machines, 3 water-powered machines and a single machine operated by hand. We show the productivities on Figure B.5, where we contrast them with the average productivity of a worker threshing with a flail, as estimated by Clark (1987). Our data is too sparse to provide precise measures of relative productivity. However, the differences are stark, and they suggest that horse-powered threshing machines may have been 5 times more productive than manual threshing, and water-powered threshing machines more than 10 times more productive. The estimates also suggest that threshing machines operated with human force did not save as much as other types of machines, and did not offer labor savings.[37] Available information also suggest that water-power threshing machines were significantly more productive than horse-powered, possibly by a factor of two.

[36] In the 1794 General View of Banffshire, Donaldson notes: "Threshing-mills have also been introduced of late, and the advantages of them seem to be so well known and established, that there is no doubt of their soon coming into general use" (Donaldson, 1794, p. 20).

[37] We only found two hand-powered threshing machines, both in Berkshire (Mavor, 1813). On the first, the informant observes that: "This machine in its present form is evidently more curious than useful. Without horses it is impossible to produce a saving." About the second, he notes: "The only saving Mr. Tull finds in its use is in making reed for thatching." Available information allows to estimate productivity only for one of these two machines.

Figure B.5: Threshing machine productivity relative to manual threshing.



Notes. Data for threshing machine comes from the county surveys of the *General View of Agriculture.* Sample size is 3 water-powered threshing machines, 24 horse-powered threshing machines and 1 men-powered threshing machine. We only consider wheat threshed and convert every quantity in bushels. We assume an 8-hours day of work when the surveys report average grains threshed per day. When farmers used women or children to operate these machines we assume that both women and children cost half of what a man does. This is likely to bias productivity downwards, as figures from the Poor Law Report suggest that on average a woman (child) was paid 37.5% (25%) of what men were paid. Average productivity of manual threshers comes from Clark (1987) who uses primary sources to estimate average productivity of English threshers in 1800s.

B.4 Historical weather in England and Wales

We compute a cereal suitability index with weather records from Hijmans et al. (2005). One possible concern with this procedure is that it uses average weather conditions for the period 1961-1990, which may be different from weather conditions that affected cereal suitability at the beginning of 1800. To determine how much weather changed over the last 200 years we perform two separate tests.

In the first one, we use historical records of temperature and precipitation on a 0.5°× 0.5°grid that covers Europe[38] to compare average temperature and precipitation in the period 1801-1830 and 1961-1990. The four panels of Figure B.6 plot average temperature in the years 1801-1830 (on the x-axes) against the average temperature in the period 1961-1990 (on the y-axes) for the four seasons of the year across the 135 cells that cover England and Wales. The four panels of Figure B.7 repeat the exercise for precipitation, and Table B.8 reports correlations for the two variables. The data suggest that weather did not change much across England in the last 200 years. In any given season, cells that were on average colder (wetter) in 1800-1830, are still so in 1960-1990. Moreover, the correlation between the two periods of average temperature (precipitation) is always above 99% (98%).

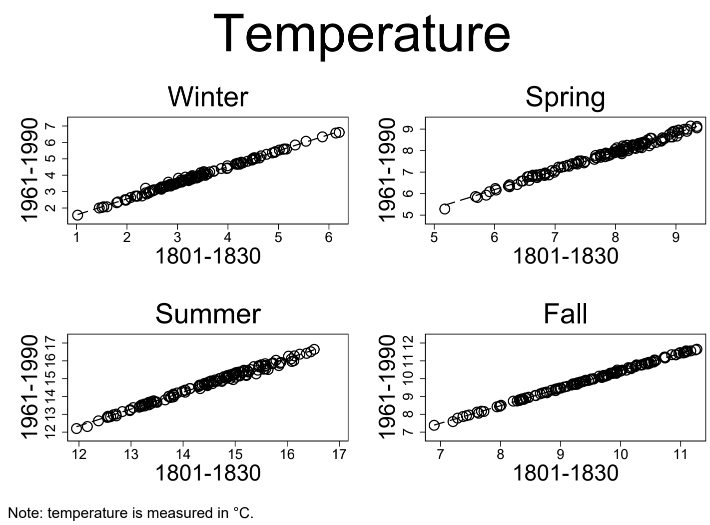
Table B.8: Correlation between weather in 1801-1830 and weather in 1961-1990.

	Temperature	Precipitation
Winter	99.78%	99.48%
Spring	99.45%	98.68%
Summer	99.50%	99.13%
Fall	99.95%	98.69%
Observations	135	135

Notes. The first column reports the correlation for temperature and the second column for precipitation. All correlations are significant at < 0.001 level.

[38] Luterbacher et al. (2004) and Xoplaki et al. (2005) describe the construction of temperature records, and Pauling et al. (2006) describe the construction of precipitation data.

Figure B.6: Average temperature by season.

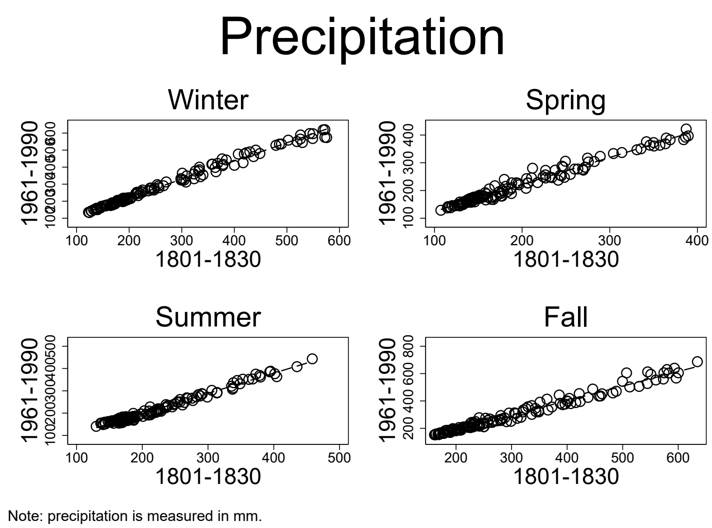


Notes. The figure plots average temperature across England and Wales in the period 1801-1830 (on the x-axes) against the average temperature in the period 1961-1990 (on the y-axes) for the four seasons of the year. Source: Luterbacher et al. (2004) and Xoplaki et al. (2005).

One possible concern with this analysis is that historical weather data are estimated rather that observed. Moreover, data are available only for separate seasons, not for separate months. To address this concern we perform a second test, using the historical series maintained by the Hadley Centre at the UK Meteorological Office. The office collects monthly precipitation records across England and Wales since 1700. Thus, it allows to compare monthly records obtained from actual observations. We use these data to compare the average monthly precipitation during 1801-1830 with the average monthly precipitation in the years 1961-1990. Figure B.8 plots these averages for the two periods along with their 95 percent intervals.

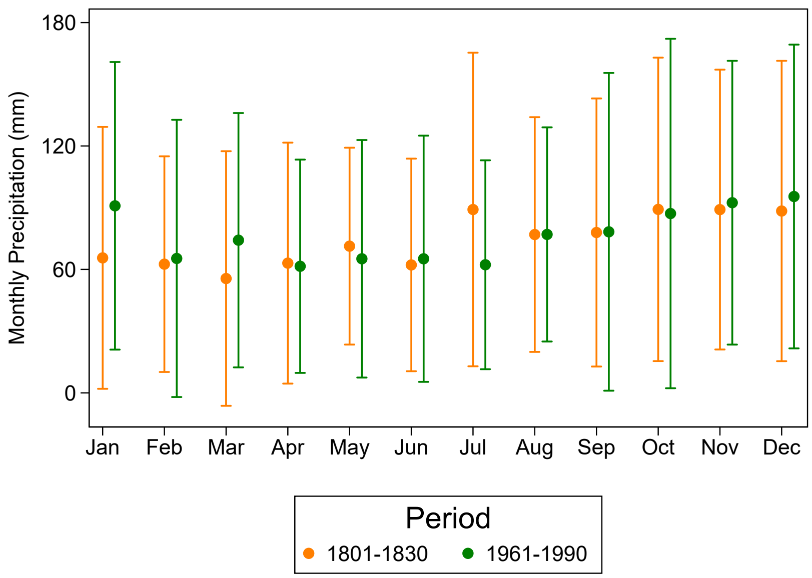
The graph confirms that precipitation did not change much in England over the last 200 years: average yearly precipitation is not significantly different in 1961-90 relative to the 30 years leading to the Swing riots. Unfortunately, precipitation is the only weather variable for which the Hadley Centre preserves historical records. Moreover, these records are admittedly noisy, as they are available only for the whole England. Nevertheless, the analysis of these records, together with the previous analysis, suggest that weather in 1961-1990 is a valid proxy for weather at the beginning of 1800.

Figure B.7: Average precipitation by season.



Notes. The figure plots average precipitation across England and Wales in the period 1801-1830 (on the x-axes) against the average temperature in the period 1961-1990 (on the y-axes) for the four seasons of the year. Source: Pauling et al. (2006).

Figure B.8: Precipitation by month.



Notes. The figure plots the average monthly precipitation across England and Wales over the period 1801-1830 (in orange) and over the period 1961-1990 (in green). The bar identify 95 percent intervals. The average yearly precipitation in 1801-1830 was 891mm: this is not significantly different from the average yearly precipitation in 1961-1990, which was 915m (difference: 23,96 mm, s.e.: 24.72). Source: Hadley Centre at the Meteorological Office: http://www.metoffice.gov.uk/hadobs/hadukp/.

C Robustness

In this section we show the robustness of our results.

C.1 Alternative specifications and estimation methods

In our baseline results, we control for 1801 Census variables and use OLS to document the effect of threshing machine adoption on riots. This specification has two limitations. First, it does not consider enclosures nor temporary weather shocks as potential causes of Swing. Second, it does not take into account the discrete nature of the dependent variable. We deal with these concerns in Table C.1.

In cols. 1-2 of Table C.1 we control for 1800 enclosure and abnormal weather conditions in 1830. Point estimates are barely effected and remain highly significant. We do not include these controls in the baseline specification because enclosures are available only for 2/3 of the sample, and historical weather has very high spatial correlation which may bias standard errors downwards.

Col. 3-4 of Table C.1 we estimate Poisson regressions. With parish controls (col. 3) or with controls and region fixed effects (col. 4) results remain robust. Finally, in col. 5-8 we look at the extensive margin of riots, and use as a dependent variable a dummy for having at least one incident in 1830-32. Col. 5-6 report results from a linear probability model: in this specification threshers strongly predict riots. In col. 7-8, we use probit estimation to account for the dichotomous nature of the dependent variable. With or without region fixed effects, we always find significant results.

Table C.1: Robustness to different estimation methods.

	No. of Swing riots				=1 if Swing riot			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Poisson	Poisson	LPM	LPM	Probit	Probit
No. of threshers	0.437	0.397	0.576	0.460	0.108	0.089	0.383	0.295
	[0.084]	[0.085]	[0.060]	[0.058]	[0.016]	[0.016]	[0.050]	[0.049]
log 1801 density	0.182	0.179	0.218	0.192	0.036	0.035	0.145	0.138
	[0.022]	[0.022]	[0.030]	[0.032]	[0.005]	[0.005]	[0.019]	[0.019]
Share of agricultural workers in 1801	0.051	0.031	-0.258	-0.279	-0.047	-0.043	-0.231	-0.242
	[0.058]	[0.056]	[0.172]	[0.163]	[0.014]	[0.014]	[0.070]	[0.071]
log 1801 sex ratio	-0.164	-0.161	-0.529	-0.553	-0.054	-0.059	-0.254	-0.268
	[0.053]	[0.053]	[0.107]	[0.109]	[0.018]	[0.019]	[0.085]	[0.091]
log distance to Elham	0.021	0.130	-0.699	-0.376	-0.113	-0.055	-0.454	-0.197
	[0.077]	[0.078]	[0.037]	[0.062]	[0.007]	[0.010]	[0.024]	[0.034]
log distance to newspaper	0.021	0.018	0.063	0.090	0.002	0.003	-0.004	0.010
	[0.023]	[0.025]	[0.054]	[0.063]	[0.005]	[0.006]	[0.024]	[0.027]
Abnormal precipitation in spring 1830	-0.012	-0.012						
	[0.003]	[0.003]						
Abnormal precipitation in summer 1830	0.002	0.003						
	[0.002]	[0.002]						
Abnormal temperature in fall 1830	-0.630	-0.076						
	[0.855]	[0.971]						
Share of land enclosed in 1800	0.011	0.008						
	[0.004]	[0.004]						
Constant	-0.431	-1.317	1.414	-0.646	0.618	0.296	0.830	-0.652
	[0.277]	[0.386]	[0.272]	[0.450]	[0.045]	[0.065]	[0.170]	[0.238]
Region fixed effects (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.048	0.055			0.067	0.083		
Mean share	0.345	0.345	0.308	0.308	0.145	0.145	0.145	0.145
Observations	6715	6715	9674	9674	9674	9674	9674	9674

Standard errors in brackets

Notes: Robustness: alternative estimation methods. Col. 1-4: dependent variable is number of Swing riots. Col. 5-8: dependent variable is a dummy for at least one Swing riot. Col. 1-2 and 5-6: OLS regressions. Col. 3-4: Poisson regression. Col. 7-8: Probit regression. Robust standard errors in brackets.

C.2 Spatial autocorrelation

In Section 2, we base inference on conventional robust standard errors that do not account for spatial correlation in the explanatory variable. However, the geographic distribution of machines and riots, as well as soil suitability, suggest some spatial correlation. Here, we show that accounting for spatial correlation has no effect on the significance of our results.

We control for spatial correlation in two ways. First, we compute standard errors with the formula proposed by Conley (1999).[39] We experiment with three different cutoffs: 20, 50 and 100 km. Second, we estimate standard errors in a non-parametric way, and estimate cluster-robust standard errors. We consider 3 different levels of clustering: closest market town, closest city that publishes a newspaper and county. This creates respectively 174, 60 and 54 clusters.

Table C.2 reports the results. OLS results remain strong and significant when we introduce Conley standard errors or clustering. Similarly, first stage, reduced form and IV results survive when we account for spatial correlation: spatially robust standard errors tend to be larger than conventional robust standard errors, but all estimates remain significant at the 2.8 percent level or better. All in all, these results suggest that spatial autocorrelation is not responsible for the significance of our findings.

[39]We estimate these standard errors the code `acreg` of Colella et al. (2019).

Table C.2: Robustness: standard errors robust to spatial autocorrelation.

No. of	Swing riots		threshers		Swing riots			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
No. of threshers	0.389	0.353					6.361	6.557
Huber-Ecker-White robust s.e.	[0.071]	[0.071]					[1.616]	[1.768]
Conley (1999) s.e.: cutoff = 20km	[0.095]	[0.088]					[2.902]	[2.948]
Conley (1999) s.e.: cutoff = 50km	[0.095]	[0.088]					[2.813]	[2.762]
Conley (1999) s.e.: cutoff = 100km	[0.110]	[0.094]					[3.062]	[3.224]
Clustered s.e.: closest market town (174)	[0.085]	[0.075]					[2.528]	[2.660]
Clustered s.e.: closest town with newspaper (60)	[0.083]	[0.081]					[2.490]	[2.747]
Clustered s.e.: county (56)	[0.096]	[0.090]					[2.878]	[2.736]
Share of area in parish whose soil is heavy			-0.034	-0.033	-0.218	-0.214		
Huber-Ecker-White robust s.e.			[0.008]	[0.008]	[0.026]	[0.027]		
Conley (1999) s.e.: cutoff = 20km			[0.011]	[0.011]	[0.039]	[0.037]		
Conley (1999) s.e.: cutoff = 50km			[0.015]	[0.013]	[0.049]	[0.042]		
Conley (1999) s.e.: cutoff = 100km			[0.017]	[0.014]	[0.062]	[0.050]		
Clustered s.e.: closest market town (174)			[0.013]	[0.012]	[0.046]	[0.041]		
Clustered s.e.: closest town with newspaper (60)			[0.014]	[0.013]	[0.050]	[0.041]		
Clustered s.e.: county (56)			[0.016]	[0.013]	[0.052]	[0.042]		
log 1801 density & parish characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects (5)	No	Yes	No	Yes	No	Yes	No	Yes
Mean dependent variable	0.308	0.308	0.062	0.062	0.308	0.308	0.308	0.308
Observations	9671	9671	9671	9671	9671	9671	9671	9671

Notes: Robustness: correction for spatial correlation. Point estimates from Table 1. Standard errors underneath estimates. Row 1: heteroschedastic-robust standard errors. Rows 2-4: standard error corrected with the formula of Conley (1999). Cutoff is 20 (row 2) 50 (row 3) and 100 Km (row 4). Rows 5-7: cluster-robust standard errors. Clustering at: closest market town (row 5), closest city with a newspaper (row 6) and county (row 7). Col. 1-2: OLS estimates of Equation (1). Col. 3-4: first stage estimates of Equation (2). Col. 5-6: reduced form estimates. Col. 7-8: IV estimates of Equation (1), using share of heavy soil as instrument.

C.3 County fixed effects and nearest neighbor matching

All our results are robust to introducing 54 county fixed effects or estimating treatment effects based on nearest neighbor matching.

Table C.3 reports results with county fixed effects. The first 4 columns report the basic correlation between riots and threshing machines. Whether we estimate OLS or a Poisson regression (col. 1-2) or we take a dummy for the presence of Swing and estimate a linear probability model or a Probit (col. 3-4), we always find strong correlations between riots and threshers. We report first stage, reduced form and IV in col. 5-7 of the same table: also these results remain strong after the inclusion of county fixed effect.

Table C.4, panel (a) estimates the average treatment effect of threshers on riots with nearest neighbor matching. Treatment is the presence of at least one thresher: we match each treated parish based on latitude and longitude. We report results when we find a single match (col. 1 and 4), 3 (col. 2 and 5) or 5 matches (col. 3 and 6). In col. 4-6 we also force matched parishes to lie within the same county. In all specifications we find that threshers are a significant predictor of unrest.

Table C.4, panel (b) estimates nearest neighbor matching with heavy soil as treatment. Treated parishes are all those in the top quartile in the distribution of heavy soils. We always match on latitude and longitude, and col. 4-6 we also force matched parishes to lie within the same county. Results confirm that parishes with heavy soils have significantly less riots.

Counties constitute small geographical units with very homogeneous agricultural systems. Moreover, close parishes share many unobserved characteristics that may bias our estimates. Because even within these fine geographical units we find that threshers cause more riots, we conclude that unobservables are unlikely to drive our results.

Table C.3: Robustness: county fixed effects.

	Swing riots		=1 if Swing		Threshers	Swing riots	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	Poisson	LPM	Probit	FS	RF	2SLS
No. of threshers	0.324	0.374	0.080	0.273			4.423
	[0.069]	[0.063]	[0.015]	[0.051]			[1.703]
Share of area in parish whose soil is heavy					-0.028	-0.122	
					[0.009]	[0.030]	
Cereal suitability index					-0.139	-0.365	0.251
					[0.045]	[0.158]	[0.350]
log 1801 density	0.147	0.350	0.051	0.232	0.020	0.155	0.065
	[0.021]	[0.036]	[0.005]	[0.023]	[0.004]	[0.022]	[0.042]
Share of agricultural workers in 1801	-0.082	-0.346	-0.049	-0.267	-0.033	-0.090	0.054
	[0.044]	[0.160]	[0.014]	[0.075]	[0.011]	[0.045]	[0.083]
log 1801 sex ratio	-0.143	-0.434	-0.044	-0.236	-0.003	-0.137	-0.124
	[0.044]	[0.118]	[0.019]	[0.095]	[0.014]	[0.045]	[0.070]
log distance to Elham	-0.067	-0.141	-0.035	-0.127	-0.006	-0.062	-0.037
	[0.114]	[0.114]	[0.027]	[0.080]	[0.013]	[0.114]	[0.126]
log distance to newspaper	0.047	0.159	0.006	0.030	0.008	0.051	0.014
	[0.026]	[0.064]	[0.007]	[0.030]	[0.007]	[0.026]	[0.041]
Constant	-0.250	-19.854	0.023	-5.510	0.091	0.061	-0.342
	[0.666]	[3.783]	[0.163]	[0.500]	[0.085]	[0.673]	[0.759]
County fixed effects (54)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.101		0.117		0.052	0.096	
Mean DV	0.308	0.308	0.145	0.154	0.062	0.308	0.308
F-test excluded instrument					9.3		
Rubin-Anderson test (p)							0.000
Observations	9674	9674	9674	9100	9674	9674	9674

Notes: Robustness: County fixed effect. Col. 1-2: dependent variable is number of Swing riots. Col. 3-4: dependent variable is a dummy for at least one Swing riot. Col. 5: dependent variable is number of threshers. Col. 6-7: dependent variable is number of Swing riots. Col. 1 and 3: OLS regressions. Col. 2: Poisson regression. Col. 4: Probit regression. Col. 5: first stage estimates of Equation (2). Col. 6: reduced form estimates. Col. 7: IV estimates of Equation (1), using share of heavy soil as instrument. Robust standard errors in brackets.

Table C.4: Nearest neighbor matching.

Panel (a): treatment = thresher	No. of Swing riots					
ATT	0.413	0.437	0.388	0.434	0.423	0.380
	[0.083]	[0.069]	[0.067]	[0.080]	[0.069]	[0.068]
Panel (b): treatment = heavy soil	**No. of Swing riots**					
ATT	-0.105	-0.075	-0.081	-0.113	-0.086	-0.093
	[0.039]	[0.028]	[0.027]	[0.041]	[0.029]	[0.027]
Number of matches	1	3	5	1	3	5
Matched within county? (54)	No	No	No	Yes	Yes	Yes
Observations	9674	9674	9674	9674	9674	9674

Notes: Robustness: nearest neighbor matching. Dependent variable is number of Swing riots. Panel (a): treated parishes have at least one thresher. Panel (b): treated parishes have share of heavy soil in the top quartile of the distribution. Col. 1-3: matching on latitude and longitude. Col. 4-6: matching on latitude, longitude and county (exact). Number of matches: 1 (col. 1 and 4), 3 (col. 2 and 5) and 5 (col. 3 and 6).

C.4 Sample restrictions

Part of the information we use to track machine adoption comes from historical newspapers. These newspapers come from 60 towns and cities, and they were more likely to advertise farm sales near the place of publication. Similarly, part of the riot data come from newspapers, and may be more likely to report unrest in the same surrounding villages. To control for this possible confounding mechanism, we include the distance to the closest newspaper in all our regressions. Additionally, here we show that all our results survive if we restrict the sample to parishes within 30 kilometers from the closest newspaper. We report our estimates on Table C.5. This table show estimates for OLS (columns 1-2), first stage (columns 3-4), reduced form (columns 5-6) and IV (columns 7-8). These estimates confirm that none of our results is driven by the potentially uneven coverage of English parishes offered by 1800 newspapers.

A second concern involves the timing of the riots. While Holland (2005) records episodes that happened until the end of 1832, most of the protests took place during the winter of 1830-31, and the most violent part of the revolt was over by the spring of 1831. Including later unrest episodes may introduce noise. To address this concern, we replicate the whole analysis after excluding all episodes that happened after April 1831.[40] Results in Table C.6 confirm that the specific definition of riots is not driving our results.

A third concern has to do with the urban nature of some of the parishes in our sample. Around 3.4 percent of the English parishes have a share of workers employed in agriculture below 10 percent: these places were mostly urban, and in 1801 they were home to about 40 percent of the English population. Because threshing machines affected agricultural workers and Swing was mostly a rural uprising, it is useful to evaluate whether our results hold when we remove urban parishes from the sample. Table C.7 reports results for parishes with agricultural share greater than 10 percent: coefficients are similar to our baseline estimates.

A final concern with our results is that they may reflect the contrast between English and Welsh parishes. English parishes specialized in cereal production and bore the brunt of the Swing riots. In contrast, pastoral agriculture was more common in Wales, and the riots left this region almost untouched. We already show that all results are robust to including 54 county fixed effects. Table C.8 shows that excluding the 949 Welsh parishes from our regressions further strengthens our results.

[40] This excludes 619 episodes, leaving 2421 riots.

Table C.5: Robustness: sample excludes parishes farther than 30 Km from a town with a newspaper.

No. of	Swing riots		threshers		Swing riots			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
No. of threshers	0.399	0.367					8.631	9.509
	[0.083]	[0.083]					[2.919]	[3.672]
Share of area in parish whose soil is heavy			-0.029	-0.025	-0.249	-0.241		
			[0.009]	[0.010]	[0.032]	[0.032]		
Cereal suitability index			0.057	0.101	0.203	0.481	-0.289	-0.483
			[0.043]	[0.044]	[0.131]	[0.137]	[0.450]	[0.621]
log 1801 density	0.101	0.098	0.012	0.010	0.103	0.097	0.002	-0.001
	[0.021]	[0.022]	[0.004]	[0.004]	[0.022]	[0.022]	[0.047]	[0.052]
Share of agricultural workers in 1801	-0.116	-0.109	-0.026	-0.033	-0.127	-0.120	0.095	0.196
	[0.050]	[0.049]	[0.012]	[0.012]	[0.050]	[0.049]	[0.131]	[0.167]
log 1801 sex ratio	-0.215	-0.226	-0.036	-0.022	-0.228	-0.236	0.082	-0.031
	[0.050]	[0.051]	[0.017]	[0.017]	[0.052]	[0.053]	[0.176]	[0.178]
log distance to Elham	-0.311	-0.228	-0.004	0.059	-0.326	-0.240	-0.291	-0.802
	[0.032]	[0.050]	[0.004]	[0.008]	[0.036]	[0.052]	[0.053]	[0.216]
log distance to newspaper	0.039	0.030	-0.001	-0.004	0.048	0.041	0.058	0.076
	[0.029]	[0.030]	[0.008]	[0.008]	[0.030]	[0.030]	[0.073]	[0.080]
Constant	1.502	1.093	0.031	-0.345	1.581	1.018	1.311	4.295
	[0.198]	[0.293]	[0.039]	[0.051]	[0.198]	[0.295]	[0.377]	[1.370]
Region fixed effects (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.053	0.060	0.006	0.030	0.050	0.059		
Mean dependent variable	0.337	0.337	0.063	0.063	0.337	0.337	0.337	0.337
F-test excluded instrument			9.3	7.1				
Rubin-Anderson test (p)							0.000	0.000
Observations	7396	7396	7396	7396	7396	7396	7396	7396

Notes: Robustness: sample excludes all parishes further than 30 Km from a city that publishes at least 1 newspaper. Col. 1-2: OLS estimates of Equation (1). Col. 3-4: first stage estimates of Equation (2). Col. 5-6: reduced form estimates. Col. 7-8: IV estimates of Equation (1), using share of heavy soil as instrument. Robust standard errors in brackets.

Table C.6: Robustness: sample excludes riots after april 1831.

No. of	Swing riots		threshers		Swing riots			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
Threshers	0.313	0.279					4.922	5.008
	[0.063]	[0.063]					[1.294]	[1.402]
Share of area in parish whose soil is heavy			-0.034	-0.033	-0.168	-0.163		
			[0.008]	[0.008]	[0.024]	[0.024]		
Cereal suitability index			0.050	0.044	0.192	0.300	-0.052	0.079
			[0.032]	[0.032]	[0.082]	[0.085]	[0.192]	[0.193]
log 1801 density	0.075	0.074	0.015	0.013	0.076	0.073	0.004	0.007
	[0.015]	[0.015]	[0.004]	[0.004]	[0.015]	[0.015]	[0.027]	[0.027]
Share of agricultural workers in 1801	-0.018	-0.017	-0.015	-0.022	-0.026	-0.024	0.049	0.087
	[0.040]	[0.039]	[0.010]	[0.010]	[0.040]	[0.039]	[0.065]	[0.071]
log 1801 sex ratio	-0.174	-0.174	-0.024	-0.011	-0.180	-0.184	-0.062	-0.128
	[0.038]	[0.039]	[0.014]	[0.014]	[0.039]	[0.040]	[0.080]	[0.077]
log distance to Elham	-0.285	-0.181	-0.006	0.070	-0.299	-0.186	-0.268	-0.536
	[0.025]	[0.040]	[0.004]	[0.007]	[0.027]	[0.041]	[0.033]	[0.109]
log distance to newspaper	0.017	0.013	-0.000	-0.000	0.018	0.016	0.020	0.016
	[0.015]	[0.017]	[0.005]	[0.006]	[0.015]	[0.017]	[0.029]	[0.032]
Constant	1.420	0.846	0.036	-0.399	1.477	0.804	1.299	2.801
	[0.138]	[0.225]	[0.032]	[0.045]	[0.139]	[0.226]	[0.199]	[0.656]
Region fixed effects (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.050	0.055	0.006	0.032	0.046	0.053		
Mean dependent variable	0.244	0.244	0.062	0.062	0.244	0.244	0.244	0.244
F-test excluded instrument			17.7	15.9				
Rubin-Anderson test (p)							0.000	0.000
Observations	9674	9674	9674	9674	9674	9674	9674	9674

Notes: Robustness: only riots between August 1830 and April 1831. Col. 1-2: OLS estimates of Equation (1). Col. 3-4: first stage estimates of Equation (2). Col. 5-6: reduced form estimates. Col. 7-8: IV estimates of Equation (1), using share of heavy soil as instrument. Robust standard errors in brackets.

Table C.7: Robustness: sample excludes urban parishes.

No. of	Swing riots		threshers		Swing riots			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
Threshers	0.375	0.327					6.547	6.652
	[0.076]	[0.076]					[1.885]	[2.031]
Share of area in parish whose soil is heavy			-0.029	-0.028	-0.191	-0.186		
			[0.008]	[0.008]	[0.026]	[0.026]		
Cereal suitability index			0.055	0.053	0.076	0.196	-0.285	-0.155
			[0.032]	[0.032]	[0.086]	[0.088]	[0.252]	[0.255]
log 1801 density	0.120	0.122	0.015	0.013	0.126	0.125	0.026	0.036
	[0.017]	[0.017]	[0.005]	[0.005]	[0.017]	[0.017]	[0.043]	[0.042]
Share of agricultural workers in 1801	0.028	0.028	-0.009	-0.015	0.023	0.025	0.085	0.127
	[0.044]	[0.044]	[0.011]	[0.011]	[0.045]	[0.044]	[0.082]	[0.088]
log 1801 sex ratio	-0.099	-0.098	-0.007	0.003	-0.099	-0.102	-0.050	-0.121
	[0.042]	[0.042]	[0.015]	[0.016]	[0.042]	[0.043]	[0.105]	[0.107]
log distance to Elham	-0.309	-0.168	-0.005	0.063	-0.315	-0.164	-0.282	-0.583
	[0.026]	[0.039]	[0.004]	[0.007]	[0.028]	[0.041]	[0.037]	[0.136]
log distance to newspaper	0.029	0.023	0.000	0.001	0.029	0.025	0.028	0.020
	[0.014]	[0.016]	[0.005]	[0.005]	[0.014]	[0.016]	[0.032]	[0.037]
Constant	1.375	0.596	0.015	-0.375	1.461	0.572	1.364	3.066
	[0.152]	[0.242]	[0.033]	[0.047]	[0.152]	[0.240]	[0.254]	[0.854]
Region fixed effects (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.057	0.067	0.004	0.027	0.052	0.064		
Mean dependent variable	0.272	0.272	0.058	0.058	0.272	0.272	0.272	0.272
F-test excluded instrument			13.9	12.4				
Rubin-Anderson test (p)							0.000	0.000
Observations	8747	8747	8747	8747	8747	8747	8747	8747

Notes: Robustness: sample excludes all parishes with less than 10% of agricultural workers in 1801. Col. 1-2: OLS estimates of Equation (1). Col. 3-4: first stage estimates of Equation (2). Col. 5-6: reduced form estimates. Col. 7-8: IV estimates of Equation (1), using share of heavy soil as instrument. Robust standard errors in brackets.

Table C.8: Robustness: sample excludes Welsh parishes.

No. of	Swing riots		threshers		Swing riots			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
Threshers	0.397	0.366					6.571	7.781
	[0.073]	[0.073]					[1.608]	[2.475]
Share of area in parish whose soil is heavy			-0.040	-0.030	-0.260	-0.231		
			[0.009]	[0.009]	[0.030]	[0.030]		
Cereal suitability index			0.070	0.064	0.209	0.440	-0.248	-0.057
			[0.040]	[0.040]	[0.119]	[0.128]	[0.319]	[0.390]
log 1801 density	0.107	0.105	0.016	0.015	0.108	0.105	0.005	-0.009
	[0.019]	[0.020]	[0.004]	[0.004]	[0.019]	[0.020]	[0.037]	[0.047]
Share of agricultural workers in 1801	-0.061	-0.059	-0.010	-0.021	-0.068	-0.068	-0.003	0.094
	[0.050]	[0.049]	[0.012]	[0.012]	[0.051]	[0.049]	[0.089]	[0.111]
log 1801 sex ratio	-0.214	-0.220	-0.036	-0.019	-0.221	-0.230	0.013	-0.083
	[0.048]	[0.049]	[0.016]	[0.016]	[0.049]	[0.050]	[0.121]	[0.135]
log distance to Elham	-0.312	-0.219	-0.001	0.070	-0.320	-0.233	-0.315	-0.776
	[0.030]	[0.046]	[0.004]	[0.007]	[0.033]	[0.049]	[0.041]	[0.179]
log distance to newspaper	0.041	0.027	0.008	0.004	0.045	0.027	-0.005	-0.004
	[0.022]	[0.023]	[0.006]	[0.007]	[0.022]	[0.023]	[0.049]	[0.058]
Constant	1.464	0.983	-0.028	-0.431	1.531	0.960	1.714	4.317
	[0.172]	[0.262]	[0.038]	[0.048]	[0.172]	[0.264]	[0.305]	[1.193]
Region fixed effects (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.051	0.057	0.007	0.031	0.048	0.055		
Mean dependent variable	0.344	0.344	0.067	0.067	0.344	0.344	0.344	0.344
F-test excluded instrument			18.9	10.9				
Rubin-Anderson test (p)							0.000	0.000
Observations	8591	8591	8591	8591	8591	8591	8591	8591

Notes: Robustness: sample excludes all Welsh parishes. Col. 1-2: OLS estimates of Equation (1). Col. 3-4: first stage estimates of Equation (2). Col. 5-6: reduced form estimates. Col. 7-8: IV estimates of Equation (1), using share of heavy soil as instrument. Robust standard errors in brackets.